Department of Electrical Engineering and Automation

Optimizing Demand Response of Aggregated Residential Energy Storages

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Abstract

The increase in uncontrollable volatile renewable generation leads to a growing need for flexibility also on the consumption side of electricity. Residential consumers, especially with energy storages such as water heaters and batteries, could shift and curtail their energy consumption. However, in order to provide suitable changes to the consumption profiles of the consumers, appropriate methods for control and incentives have to be developed. This thesis presents several developed optimization methods for an aggregating retailer to aggregate multiple mostly independently acting consumers for diverse market participation. The first set of contributions included methods for planning aggregate consumptions schedules for the day-ahead market, as well as for taking into account the potential intra-day flexibility of the optimized schedules. In addition, analysis were made on how much the aggregator can shift the consumption of its consumers depending on whether the consumption is responsive to changes in prices or if the aggregator can directly alter the consumption. Secondly, the participation of residential consumption in frequency control was considered. Centralized control was simulated utilizing a proposed agent-based model, under uncertain communication latencies. Furthermore, methods were proposed for optimizing day-ahead schedules for participation in the frequency reserve market. The optimization frameworks were extended to include various uncertainties in the resulting electricity demand and market prices, as well as coordination of charging and reserve participation plans between the consumers under the different conditions. In order to test the various developed methods, multiple stochastic programming models are devised and simulated for large populations of residential consumers. The results indicate that flexibility of residential consumption could potentially be utilized for participation in the wholesale market, intra-day trading and frequency reserves. Furthermore, the performed simulations illustrate the benefit of considering flexibility during the day-ahead planning of electricity consumption.

Tiivistelmä

Volatiilien uusiutuvien energialähteiden kasvava osuus energiantuotannusta johtaa tarpeeseen saada myös sähkönkulutus joustamaan tarvittaessa. Esimerkiksi yksityisasuntojen sähkönkulutusta voisi hetkellisesti siirtää, varsinkin jos käytössä on energiavarastoja kuten esimerkiksi vedenlämmittimiä ja akkuja. Jotta sopivia muutoksia kuluttajien sähkönkulutukseen saataisiin, on kuitenkin tarpeen kehittää ohjaus-, optimointi- ja insentiiviratkaisuja. Tässä väitöskirjassa esitetään muutamia uusia optimointimenetelmiä, joita esimerkiksi sähkön vähittäismyyjä voisi käyttää aggregoimaan osin itsenäisesti toimivia kuluttajia monipuolisesti useille markkinoille. Ensimmäinen osa kontribuutioita sisältää menetelmiä, joilla voidaan optimoida kulutusaikatauluja vuorokausimarkkinoille sekä ottaa samalla huomioon potentiaali päivänsisäiseen kauppaan. Lisäksi analysoitiin kuinka paljon kulutusta voidaan saada joustamaan riippuen siitä optimoivatko kuluttajat itsenäisesti ja reagoivat muutoksiin heidän sähkön hinnassa, vai ohjaako aggregaattori niitä suoremmin. Toisessa osassa kontribuutioita tutkittiin sähkön kulutuksen soveltamista taajuusohjaukseen. Keskitetyn ohjauksen soveltuvuutta tutkittiin agenttipohjaisella mallilla, jota simuloitiin vaihtelevilla kommunikaatioviiveillä. Kulutuksen todettiin soveltuvan keskitettyyn taajuusohjaukseen suuremmillakin viiveillä ilman että syntyy vaarallisia värähtelyitä. Lisäksi kehitettiin menetelmiä taajuusohjausmarkkinoihin osallistumiseen optimoimalla kulutuskäyräsuunnitelmia päivämarkkinoille. Kehitetyissä optimointialgoritmeissa otettiin huomioon epävarmuuksia kulutuksessa sekä markkinahinnoissa. Stokastisia ohjelmointimalleja simuloitiin suurella määrällä kuluttajia ja skenaarioita. Simulaatioiden tulokset indikoivat että sähkönkulutuksen joustavuutta voitaisiin mahdollisesti käyttää päivä-, päivän sisäisillä sekä taajuusmarkkinoilla. Lisäksi simulaatiot havainnollistavat kuinka joustopotentiaali kannattaa ottaa huomioon suunniteltaessa kulutusta jo edellisenä päivänä.

Preface

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Helsinki, August 26, 2018,

Olli Kilkki

Contents

List of Publications

This thesis consists of an overview and of the following publications which are referred to in the text by their Roman numerals.

I Olli Kilkki, Antti Alahäivälä, Ilkka Seilonen. Optimized Control of Price-based Demand Response with Electric Storage Space Heating. *IEEE Transactions of Industrial Informatics*, Volume 11, Pages 281–288, Feb 2015.

II Olli Kilkki, Ilkka Seilonen, Kai Zenger, Valeriy Vyatkin. Incentives for Shaping the Consumption Profile of an Energy Storage Population. In *IEEE PES ISGT Europe 2016*, Ljubljana, October 2016.

III Olli Kilkki, Antti Kangasrääsiö, Raimo Nikkilä, Antti Alahäivälä, Ilkka Seilonen. Agent-based modeling and simulation of a smart grid: A case study of communication effects on frequency control. *Engineering Applications of Artificial Intelligence*, Volume 33, Pages 91–98, August 2014.

IV Antti Alahäivälä, Olli Kilkki, Merkebu Z. Degefa, Ilkka Seilonen, Matti Lehtonen. A Virtual Power Plant for the Aggregation of Domestic Heating Load Flexibility. In *IEEE PES ISGT Europe 2014*, Istanbul, October 2014.

V Olli Kilkki, Ilkka Seilonen, Valeriy Vyatkin. Optimization of Decentralized Energy Storage Flexibility for Frequency Reserves. In *IECON 2015*, Yokohama, November 2015.

VI Olli Kilkki, Kai Zenger, Ilkka Seilonen, Valeriy Vyatkin. Optimizing Residential Heating and Energy Storage Flexibility for Frequency Reserves. *International Journal of Electrical Power & Energy Sys-*

tems, *Accepted – pre-review version*, Final version at: `https://doi.` `org/10.1016/j.ijepes.2018.02.047` 2017.

Author's Contribution

Publication I: "Optimized Control of Price-based Demand Response with Electric Storage Space Heating"

This journal article presents collaborative research where the main ideas were developed with Antti Alähäivälä and the other co-authors, and the paper was written by the author.

Publication II: "Incentives for Shaping the Consumption Profile of an Energy Storage Population"

This article presents research by the author who modelled and simulated the system and wrote the bulk of the publication with help from the other collaborators.

Publication III: "Agent-based modeling and simulation of a smart grid: A case study of communication effects on frequency control"

The article presents collaborative research where the author was involved in the design of the agent-based model and the control logic of the simulator. The author wrote, in particular, the sections on frequency control and simulations.

Publication IV: "A Virtual Power Plant for the Aggregation of Domestic Heating Load Flexibility"

The author was involved as a co-author in developing the main ideas of the paper and assisting in writing the publication.

Publication V: "Optimization of Decentralized Energy Storage Flexibility for Frequency Reserves"

This article presents research by the author who modelled and simulated the system and wrote most of the publication.

Publication VI: "Optimizing Residential Heating and Energy Storage Flexibility for Frequency Reserves"

This article presents research by the author who modelled and simulated the system and wrote most of the publication.

List of Symbols

$A_n,\ \boldsymbol{b}$	Matrices and vector describing complicating constraints
$C_{n,0}$	Initial state of charge of a storage
$\overline{C}_{n,t}^{\omega_1,\omega_2}$	Expected state of charge
$C_{max,n}$	Maximum state of charge
E_t	Amount of energy to purchase from day-ahead market
$\Delta E_{\uparrow,t}^{\omega_1,\omega_2},\ \Delta E_{\downarrow,t}^{\omega_1,\omega_2}$	Imbalances from expected consumption schedule
f_n	Nominal frequency of the grid
Δf_{db}	Activation deadband for primary frequency control
Δf_{max}	Maximum activation threshold for primary frequency control.
$g(\cdot),\ g_n(\cdot)$	Objective function
H	Optimization horizon
$J_t^{\omega_1,\omega_2}$	Compensations given to consumer for their participation
K_t	Price of electricity charged from consumers
$K_{min},\ K_{max},\ \overline{K}$	Minimum, maximum and averages of electricity price
K_{flat}	Price of electricity when consumers charged a flat rate
$K_{s,t}^{\omega_1}$	Day-ahead market price
$K_{r,t}^{\omega_1}$	Day-ahead reserve price
$L_t^{\omega_1,\omega_2}$	Aggregate consumption from charging and inflexible consumption
$\delta L_t^{\omega_2}$	Aggregate imbalances resulting from inflexible consumption
N	Number of consumers/appliances
Ω	Number of scenarios in stochastic models

$P_{n,t}^{\omega_1}$	Energy storage charging
$P_t^{\omega_1}$	Aggregate energy storage charging
$\delta P_{n,t}^{\omega_1,\omega_2}$	Demand response potential
$\delta P_{\uparrow,n,t},\ \delta P_{\downarrow,n,t}$	Increase and decrease bids of a consumer for a certain time step
$\overline{\delta P}_{n,t}^{\omega_1,\omega_2}$	Average realized activation of reserve
$\pi_{\uparrow,t}^{\omega_1,\omega_2},\ \pi_{\downarrow,t}^{\omega_1,\omega_2}$	Balancing market price (increase and decrease)
π	Balancing/regulating cost/compensation relative to market price
Φ_ϵ^{-1}	Value of the standard normal inverse cumulative distribution function at a certain percentage ϵ
$Q_{n,t}^{\omega_1,\omega_2}$	Energy demand (heating)
$\sigma_{Q,n}$	Standard deviation of forecast error in demand
σ_f	Standard deviation of realized hourly frequency deviations
$T_{\uparrow,t},\ T_{\downarrow,t}$	Target schedule for frequency reserve (increase and decrease)
Δt	Time step
w	Heuristic weight in multi-objective optimization
$W_k,\ W_v$	Grid inertia constants
$\boldsymbol{x},\ \boldsymbol{x}_n,\ \boldsymbol{y}$	Vectors containing decision variables
$\mathbb{X},\ \mathbb{X}_n,\ \mathbb{Y}$	Sets of constraints

List of Abbreviations

ABMS	Agent-based modelling and simulation
ADMM	Alternating direction method of multipliers
ARMAX	Autoregressive moving average with exogenous variables
BESS	Battery energy storage system
DLC	Direct load control
DR	Demand response
DSM	Demand side management
DSO	Distribution system operator
EMS	Energy management system
EE	Energy efficiency
EV	Electric vehicle
EVP	Expected value problem
FCR-D	Frequency controlled disturbance reserve
FCR-N	Frequency controlled normal operation reserve
HVAC	Heating, ventilation and cooling
LP	Linear programming
MILP	Mixed-integer linear programming
MSE	Mean square error
QP	Quadratic programming
RTP	Real time pricing
SAA	Sample average approximation
SOC	State of charge
SP	Stochastic programming
TCA	Thermostatically controlled appliance
TOU	Time of use (pricing)
TSO	Transmission system operator
VPP	Virtual power plant

1. Introduction

The global target of a cleaner planet involves a dependence on renewable energy generation, such as wind and solar power. However, the uncontrollable intermittent renewable generation leads to an increased need for flexibility of the other participants in the electrical grid. In the imminent future, with the development of a smarter electrical grid, also the consumption of electricity is seen to be able to participate in maintaining the balance of production and consumption [1–3]. Home automation and energy management systems (EMS) in residential houses could be utilized for shifting or curtailing the consumption, without considerably affecting the desired level of comfort [4]. Also with the expected growth of electric vehicle penetration, there comes an increase in total volatile demand. The batteries in these vehicles could however further enable responsive electricity consumption [5]. In addition, the deployment of dedicated residential batteries may also see an increase in the future [6], in conjunction with local energy generation [7]. Even traditional thermal energy storages such as electric storage space heaters, water heaters, and the thermal properties of the houses themselves could be utilized for shifting and curtailing electricity consumption profiles [8, 9]. However, there are challenges to be investigated related to e.g. optimally planning and coordinating aggregate consumption schedules [10], and providing sufficient incentives for consumer cooperation [3, 11], before the potential responsiveness of demand could be fully utilized.

Currently, the hierarchical electrical grid consists of electricity production facilities, the transmission and distribution network, and electricity retailers and their customers [12]. To ensure reliable operation of the grid, the real-time balance between supply and demand of electricity has to be maintained. In practice, the balance is maintained with the cooperation of the wholesale electricity markets and independent operators. The

electricity markets match production and consumption bids, while independent operators are placed in charge of addressing the more real-time imbalances that occur due to errors in the forecasts of production and consumption [13]. In the considered Nordic market areas the operators in charge of maintaining the balance are the transmission system operators (TSOs), while similar arrangements can be identified in other areas around the globe [14, 15]. The TSO then contracts various participants that are connected to the grid to increase or decrease their production or consumption based on the current grid state. Continued imbalances between consumption and production then manifest themselves as deviations in the frequency and voltage levels of the alternating current in the electrical grid.

The modernization of the grid with new information and communications technology could enable and enhance monitorability and controllability of electricity consumption. However, suitable energy management systems for automating and monitoring the demand response would be needed to fully realize the potential, in addition to development of relevant optimization procedures and algorithms [3, 16]. In case the end-consumers are involved in the market participation and charged a dynamic price for their electricity, the term *elasticity* traditionally refers to the relative change in demand due to a change in price [13]. Conversely, the term *flexibility* is used to refer to the maximal possible changes that could be made in the amount of consumption, while not impacting the comfort level or the correct functioning of the appliances [17, 18].

The flexibility of the consumption could then be utilized on various power and energy markets, through price elasticity or more direct methods. A plausible solution for harnessing the flexibility of electricity consumption involves an aggregating entity which can be referred to as an *aggregator* [19–21], or a *virtual power plant* (VPP) [22, 23]. The entity operates in the electricity exchange and power markets for acquisition and regulation similarly to a power plant, but likewise with electricity consumption. Furthermore, the aggregator or VPP could also have small generation capacity e.g. in the form of photovoltaic panels. This aggregator would have to aggregate the small electricity consumption sources, including their uncertainties, and attempt to maximize the attainable monetary benefits using various markets. The aggregator would need to communicate and be able to affect the behaviour of the consumers it is aggregating, either directly or through pricing signals. Development of appropriate algorithms

is then required for maximizing the utilization of the consumer resources with automated control [24–26], while producing fair compensation for all the parties involved [3].

1.1 Research objectives and scope

The main problem under study in this thesis comprises of effectively utilizing the flexibility of large numbers of small consumption sources that might be independently controlled, and properly involving them in various markets. The aim of this thesis is to develop several methods for an aggregating retailer to aggregate multiple mostly independently acting consumers for diverse market participation, and examine the potential of the different approaches. The wholesale electricity and reserve markets are mainly studied as prospective application areas for the achieved flexibility. The base hypotheses were that the available flexibility of electricity consumption might be markedly affected by the level of direct control the aggregator has over the consumers, and that frequency control could be a suitable application for the flexibility. The more detailed objectives can be categorized into two parts consisting of

- at first of studying price elasticity of day-ahead consumption planning of independently optimizing consumers. In addition, the potential benefits of utilizing the flexibility of these plans by inducing further deviations to the planned schedules were investigated. The aim was to gain insights on the effects of different forms of control on the achievable flexibility.
- The second set of objectives focused on utilizing the consumption flexibility for participation in frequency control. The various challenges that were tackled included the uncertainties in the resulting control, communication and monetary compensation. The aim was to understand the potential benefits of reserve market participation.

The point of view in this thesis is mostly on an aggregating retailer which aggregates the consumption of the residential consumers and their flexibility for participation in various markets. Several timescales were considered ranging from day-ahead planning to real-time regulation, with an emphasis on coordinating the response of independently acting consumers. As the focus was on the market participation, the locational effects on the transmission or distribution levels were not taken into ac-

count. The considered aggregator acts as a price-taker, and submits single consumption and reserve participation bids reflecting its expected consumption and allocated reserve participation, respectively. The assumption was made that the relatively small amount of shiftable consumption involved will not affect the chosen electricity markets. Frequency reserve markets were specifically considered for their prevalence as suitable markets in the European setting [27, 28]. There could also be an increase in the near future in the amount of required reserves due to a relative decrease in grid inertia [29]. Furthermore, electricity consumption has been noted as a potentially good resource for frequency control both in theory [30, 31] and in real-world tests [32].

Because of the relatively large share (up to 50% [33] of total electricity demand) of heating demand in Nordic countries, and its ease of shiftability with minor loss of comfort [2], heating was chosen as the primary consumption for consideration for demand response. Energy storages were also included for the hypothetical consumers, due to their suitability [31] and prospective increased market penetration with electric vehicles and other local storage solutions [6, 7, 34]. In general, the energy storages could also represent more traditional solutions such as storage space heating or water heaters [9, 35].

In the various approaches that are explored in this thesis, it was assumed that the consumers can be communicated with and that they can forecast and control their electricity consumption schedules. The communication could be achieved through various standard communication channels and protocols, both for the controllable loads inside the houses [36–38], and through larger scale networks [39, 40]. Various energy demand models for the buildings and appliances of the consumers have already been widely researched [41–43] and are not focused on in this thesis. It was also assumed that the consumers' contract obliges them to either inform the aggregator of any real-time changes to the consumption schedules, or alternatively the aggregator has more direct control over the consumption. Considering practical implementation, also the possible benefits of increased energy efficiency were not directly considered, nor the implementation, operating or maintenance costs that would be involved with realizing the proposed techniques.

1.2 Research methodology and methods

Research on developing a smarter electrical grid has recently gathered much attention, and contains various distinct aspects that are currently being addressed in multiple sections of the research community. Some main aspects that have been indicated to require research range from the communication and standards required for interoperability [39], to surfacing computational intelligence problems, economic considerations, as well as developing suitable testbeds [44]. The research carried out for this thesis considers itself mainly with the computational intelligence, and economic research areas, in addition to considerations for some aspects relating to communication between the studied actors. The presented research utilizes simulations extensively in order to study the proposed methods.

Simulation is an essential tool in smart grid research [45] as well as modern engineering research in general [46, 47], especially when an analytical model of the studied behaviour can not be derived due to the complexity of the studied system. or alternatively in order to aid in developing policies or novel systems without disturbing the original system (i.a. the grid and electricity markets) [48, 49]. In particular, in this thesis the purpose was to develop several novel demand response (DR) methods as well as evaluate their potential in the current market conditions.

Modelling and simulation [50–52] is a methodology describing methods for constructing models and simulations in order to generate data as a basis for decision making. The models can consist of hierarchical structures with discrete and continuous systems [52]. Furthermore, the systems included in the models can be envisioned as independently acting agents with specific goals, resulting in an agent-based modelling and simulation (ABMS) approach [53]. Modelling and simulation was applied in this thesis in conjunction with the conventional research process [54] with the steps of

- identifying the problem,

- reviewing established research,

- formulating hypothesis,

- designing (i.a. optimization) models,

- solving & simulating,

- evaluating & analyzing the resulting data,

- and interpreting & presenting as publications [54].

Research methods

The main methods utilized in the research presented in this thesis consist of modelling the relevant aspects of demand response by, in most cases, formulating them as constrained optimization problems, and simulating the acquired solutions. Multiple simulations are required in order to capture the stochastic nature of the studied systems [48]. The aim in the thesis is to devise techniques for planning consumption schedules that can be modified for the purposes of various markets, while providing a sufficient level of comfort for the consumers.

During the modelling of the problems, mainly linear models are developed, with careful consideration made in determining the decision variables. The included models consist of energy demand and market behaviours, while the studied actors attempt to achieve their goals with the aid of these models. The models are then utilized in several optimization problems, that are solved using linear or stochastic programming [55] approaches. In stochastic programming, uncertainties in realized market prices and electricity demand are considered in the costs and constraints of the problem [55]. In the following, these uncertain values are modelled using models found in the literature or by estimating some of the variables for the purposes of this thesis. Furthermore, multiple stages might have to be considered during the optimization, in order to account for cases where multiple decisions have to be made in succession, and uncertainties are revealed at different times. In addition to multi-stage stochastic programming, multiple simulations on the optimized values are performed, and some sensitivity analyses, for verifying robustness of the solutions.

1.3 Contribution

The thesis consists of publications numbered I–VI, the main contributions of which could be divided into two main categories. The first category of contributions includes the development of methods for an aggregator to shape the aggregate consumption which are used for for studying the flexibility potential of independently acting consumers (PI–II). In the second category, the flexibility was aimed to be utilized for frequency reserves

and methods were developed for involving the consumption in frequency markets (PIII–VI).

Optimizing day-ahead consumption planning and rescheduling

At first the aim was to plan aggregate consumption schedules for the wholesale market and to obtain changes to those plans with further incentives for the consumers. In Publication I, a game-theoretic approach was developed for choosing the dynamic prices to charge from independently operating consumers. In addition to determining convenient day-ahead price signals, intra-day hourly discounts were devised for reshaping the consumption profile. Simulations then also provided results that illustrated how the aggregator could potentially reduce its operation costs by optimizing the day-ahead prices of its consumers and with discounts to these prices could further reduce the costs.

Then in Publication II, the focus was on examining how much the aggregator can shift the consumption of its consumers depending on whether the consumption is responsive to changes in prices or if the aggregator can directly alter the consumption. Comparisons were made between the case where the consumers independently optimize their consumption and offer bids for changing their consumption using a proposed algorithm, and cases where the aggregator can more directly alter the consumption schedules. Methods were proposed that could enable an aggregator to optimize the flexibility of its aggregate consumption, as well as a bidding algorithm for independently optimizing consumers (in PIV and PII). The performed simulations illustrate the benefit of considering flexibility during the day-ahead planning of electricity consumption.

Frequency control participation

The second set of contributions is related to enabling consumer participation in frequency control. In Publication III, centralized control of consumption was simulated utilizing a proposed agent-based model, under uncertain communication latencies. The simulations indicate that demand response could support a single large power plant outage even under the influence of relatively large communication latencies. In addition, a decentralized method was simulated to illustrate its advantages (PIII), as well as methods for operating under different network conditions from normal to emergency and restoration (PIV).

In Publication V, a heuristic optimization approach was developed for optimizing participation in frequency reserve markets while taking into account day-ahead electricity acquisition costs. A distributed optimization formulation was devised and the effects of the amount of participation on costs and their variance were explored through simulations. In Publication VI, the optimization framework of reserves participation was extended to include various uncertainties in the resulting electricity demand and market prices, as well as coordination of charging and reserve participation plans between the consumers under the different conditions. The potentially reduced costs were supported with extensive simulations of the proposed model.

1.4 Structure of the thesis

The remainder of the thesis consists of at first Chapter 2 describing prerequisite information and established relevant scientific knowledge in the field of demand response. In addition, various relevant optimization methods and utilized markets are detailed. Then, Chapter 3 overviews the models developed for this thesis, as well as the simulation results achieved in the attached publications. Discussion on the implications and future development of the research is considered in Chapter 4, while Chapter 5 presents conclusions.

2. Demand response

This chapter describes relevant background information regarding research on smart grids and demand response in particular. At first, various established approaches for controlling the consumption are outlined. Then, the relationship between the consumers and an aggregating retailer is defined, as well as the potential markets where their operation can be utilized. Furthermore, some basic principles behind the optimization methods utilized in this thesis, and smart grid research in general, are outlined.

2.1 Controlling the consumption

In practice, demand response in residential electricity consumption is currently often activated manually by deferring appliances or setting static schedules for e.g. water heaters. However, there has been a sizeable effort in the research community for developing control and optimization methods for coordinating the deferring of demand to most opportune times. The consumption can be manipulated on various timescales, and there are corresponding markets where the potential can be capitalized. Many approaches have been identified in the literature for coordinating the operation of appliances, which are outlined in the following.

2.1.1 Timescales and incentives

Demand response is one of the several demand side management (DSM) measures that can be enacted to improve the operation of the grid. For instance, the different measures can be categorized based on the timescales of their intended operation. Palensky and Dietrich [2] propose the following categories (Figure 2.1):

- Energy efficiency (EE)

- Time of use (TOU)

- Demand response (DR)

- Spinning reserve (SR)

More or less permanent energy efficiency measures such as behavioural changes and changes to equipment, are not considered in this thesis. Instead, the focus is on timescales ranging from seconds to days. Among the considered timescales, TOU tariffs are placed on certain periods (e.g. static day and night time prices) in order to motivate consumers to change their consumption patterns [2]. DR is then used to refer to more dynamic response of consumption, which can be further categorized as market-based and physical DR. Market DR refers to cases where price signals are used to invoke changes to consumption, while physical DR involves more direct control, e.g. emergency signals and continuous regulation. SR then typically refers to the unused capacity which is activated only during larger imbalances [56, 57]. In general, the regulation that occurs continuously to maintain the balance of the grid is further referred to as primary control [58] which operates on a timescale of seconds w.r.t. the frequency of the grid. These different demand-side measures can be implemented using multiple different approaches, some of which are outlined in the following, and expanded upon as well as partly compared in the research included in this thesis.
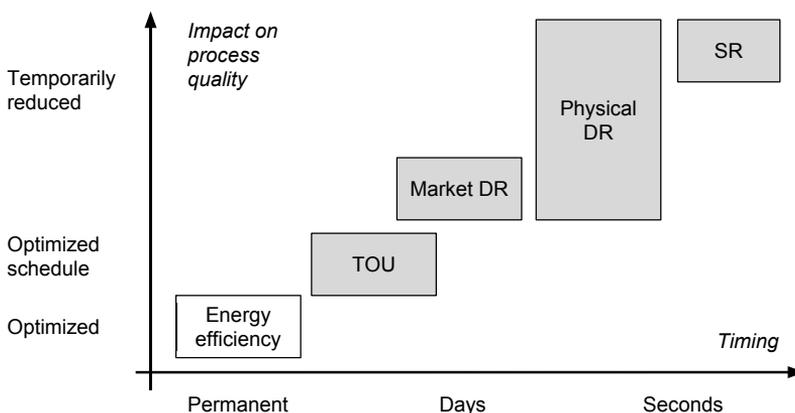
Figure 2.1. Categorization of DSM, where the shaded categories indicate the timescales that are mostly considered in this thesis. Adapted from the work by Palensky *et al.* [2].

The applicable DR programs can be classified based on the chosen control mechanism, offered motivations or decision variables [59]. The chosen approaches might have varying levels of feasibility and performance, depending on the types of consumers. The control mechanism can either be a centralized or a distributed solution, or a combination of them. In the centralized approach, the control of the electrical loads is centrally coordinated, while in the distributed schemes the loads can monitor some common value such as the grid frequency or a price signal in order to individually adjust their consumption. The centralized mechanism requires a certain level of invasiveness, as the individual states of the consumer appliances have to be centrally managed [60], whereas distributed approaches might involve iterative procedures [61–63].

Another classification is based on the method of monetary motivation offered to the consumers. The consumers could be motivated using either

- price based programs or

- incentive based programs [59].

The choice between different approaches could however influence the amount of flexibility that could be achieved and different approaches might have to be combined for effective utilization [2, 60]. In the price based programs, time based rates for electricity are devised, ranging from static TOU rates, to real time pricing (RTP) [60]. Conversely, in the alternative incentive-based schemes, the aggregator either has more or less direct access to the consumer appliances and monetary benefits are distributed later, or the EMS of the consumer can propose prices for which they would be willing to shed consumption (i.e. demand bidding). Alternatively, in classifying demand-side management programs the distinction can also be made between the decision variables that are under consideration, i.e. between scheduling and energy management-based [59]. In the scheduling-based models, the focus is on scheduling the activation of individual tasks, while in energy management-based approaches the continuous energy consumption of specific loads is increased or decreased.

2.1.2 Control algorithms

The actual control mechanism that adjusts the loads while ensuring a level of comfort, depends on the particular demand source and the required timescale of response. Demand response involving industrial loads has also been widely researched [64–66], and already utilized to some ex-

tent through interruptible load programs [67–69]. However, residential consumption can have some distinct properties that complicate its application, depending on the level of control the aggregator has on the consumers, and the available markets. The consumers should obtain some benefits from adopting load control programs, e.g. in the form of monetary payments for the individual consumption adjustments. For the aggregator, the challenge is selecting appropriate control schemes and contracts which enable adjusting the consumption profile without affecting the consumer satisfaction or incurring excessive risks, such as via uncertain electricity costs [70, 71]. The feasibility of such plans is however influenced by the preferences [72] and willingness [73] of the consumers. In addition, the consumers might potentially be concerned with decreased privacy by revealing e.g. their living habits through cooperative optimization applications where they have to disclose the constraints on their level of comfort, or even directly from inference of their consumption data [74, 75]. The practical issues, including the interruptibility, schedulability and curtailability of the controlled loads in question [76], the availability of the sufficient information on load behaviors [77], and computational and communicational issues [78], have to be also taken into consideration. Furthermore, if large changes are made to the consumption profile, a so-called *payback* (or rebound) effect can occur when the momentarily curtailed consumption has to be "paid back" [2].

Many residential loads could be aggregated for demand response and their total potential could be significant [79, 80], but they present various different constraints on their controllability. These loads can be divided between energy management-based devices that include more continuous consumption sources such as heating that can temporarily be curtailed, and alternatively scheduling-based appliances [59]. Schedulable appliances could consist of e.g. dishwashers and cloth dryers [80]. In general, when properly aggregated, groups of loads can provide a near instantaneous grid balancing response with a spatially distributed effect [81]. For example, thermostatically controlled appliances (TCA) can be coordinated to provide continuous primary control [82, 83]. The frequency of the electrical grid can especially be used to convey the current grid condition and assist in achieving a distributed control method for continuous physical DR, such as primary control [84]. Multiple diverse methods have already been developed that enable TCAs [30, 32, 84–89] and general on/off devices [32, 88, 89] to participate in frequency-based control.

The approaches for aggregate control of TCAs can be categorized into set-point control and direct control mechanisms [90]. In the set-point methods, the set-points or operating temperature ranges of the thermostats are collectively controlled to obtain changes to the level of aggregate consumption [30, 32, 83, 85, 89, 91–93]. Conversely, in direct control mechanisms [84, 87, 88], the control can be enacted by direct intervention by the aggregator or indirectly by allocating appropriately randomized frequency thresholds to the loads. When the loads receive these thresholds, they commit to increasing or decreasing their consumption in case the grid frequency exceeds the given threshold. Figure 2.2 displays the effects of these thresholds on an aggregate consumption level with varying frequency deviations. The target consumption has to vary close to proportionally to the deviations of the frequency beyond a deadband value Δf_{db} and up to a maximum deviation Δf_{max} [94]. When frequency is at its maximum or minimum deviation, the consumption reacts with a full activation δP from its nominal value. During the operation, the randomized thresholds can be occasionally reshuffled in order to distribute the activation fairly. Hysteresis and delays can also be included to avoid excessive switching. Similarly, direct charging without thermostats such as with electric vehicles could be controlled using hysteresis and varying thresholds for alternating charging [81, 82].
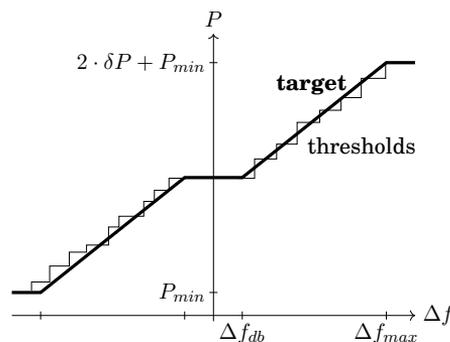
Figure 2.2. Frequency thresholds and resulting aggregate consumption for a group of loads for participation in frequency containment reserves.

Especially loads with energy storage capabilities are useful for shifting their charging without directly affecting the consumer level of comfort [31]. A need for increased energy storage capacity in the grid is justified by the growing amount of intermittent renewable generation and prospective local generation [5, 95, 96]. In addition to larger energy storages on the utility level [97, 98], residential smart grid participants could also benefit

from local storages [7, 99], that are rapidly becoming affordable [100]. In particular, scheduled charging of local microstorages, including electric vehicles [5, 101], generic batteries [7], or various thermal storages, such as TCAs [8, 102], HVAC loads (heating, ventilation and air-conditioning) [103, 104], water heaters and storage space heaters [9, 35], have been envisioned to be utilized in shaping the aggregate consumption profile.

2.2 Electricity markets

In general, an aggregating retailer attempts to predict and control the aggregate consumption profile of its consumers, while participating in electricity markets. With the Western deregulation and restructuring of electricity markets, beneficial competition with new players, including more efficient demand-side participation, can be achieved [15]. Most of European countries have comparable market structures of day-ahead and intra-day markets, as well as bilateral contracts. Similar arrangements of markets can be found also in many other areas [14].

In particular, the Nordic region (i.e. Finland, Norway, Sweden and Denmark) has a single integrated market. The various markets that can be operated on are depicted in Figure 2.3, where T denotes the current hour. The markets with darkened backgrounds represent the timescales that are mainly considered in this thesis. In the day-ahead spot market, the hourly prices are determined during the day before the operating day, based on aggregate production and consumption bids [15]. Production–consumption imbalances between the market areas are also taken into account while obeying cross-border transmission limits. Then, during the operating day, intra-day markets enable the market participants to exchange any changes they wish to make to their production and consumption profiles. Any imbalances that the participants have in their realized profiles during the delivery phase are then later settled at a cost relative to the realized exchange prices. These balance settlements are operated by the transmission system operator (TSO) [105]. The TSO aims to maintain the operational security of the transmission system as well as enhance the effective functioning of the electricity market [105]. They have to maintain the momentary balance between demand and supply by i.a. contracting reserves that are willing to react to imbalances. Additionally, the local TSO (e.g. Fingrid in Finland) attempts to maintain the production–consumption balance by purchasing balancing power at

an hourly basis [106].
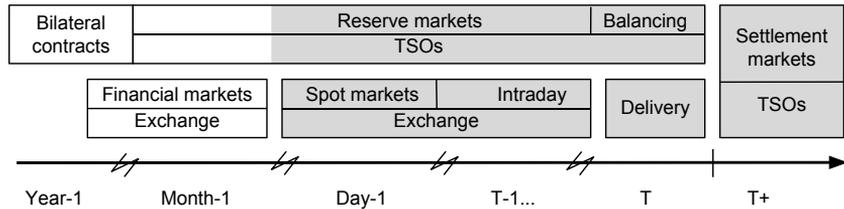
Figure 2.3. Electricity and power markets in Nordic countries, with the darkened areas
representing the timescales considered in this thesis. Adapted and extended
from the work of Oksanen *et al.* [15] to include the reserve markets, balanc-
ing operations and highlight the timescales used in this thesis.

The TSO also maintains the balance of the grid by acquiring reserves
that are then obligated to automatically or manually with instructions
from the TSO react to any imbalances by responding proportionally to
changes in the grid condition [28]. The frequency controlled reserves in-
clude the disturbance reserve (FCR-D) that has to react quickly to any
large deviations in the frequency, and the normal operation reserve (FCR-
N) that operates continuously [107]. In order to operate on these markets,
the participants have to be able to guarantee that they can increase and
decrease their consumption (or production) with the agreed amount dur-
ing all the promised hours. In Finland, these markets operate both on a
yearly and hourly basis, where the hourly market is settled daily for the
following 24 hours [108]. Most of these markets already allow at least
partly both production and demand-side contributions, and could enable
even further participation in the future [27]. For efficient participation of
consumption (and production alike), hourly bids to these markets have to
be produced [109, 110].

In the day-ahead electricity trade in the spot market, the buyers and
sellers submit bids to the relevant markets that consist of the amount of
energy that the participant pledges to sell/buy and at what cost. These
bids are then ordered according to their price and the market price is set
as the intersection point between the buy and sell bid curves [13, 111]. In
addition, bottlenecks in transmission constraints are taken into account
in setting the market prices.

In planning the the bids and thus the coming consumption schedules,
the electricity price should be at least partially predicted [13]. There
have been various models that have been developed that can provide suffi-
ciently accurate forecasts of e.g. the day-ahead price [112, 113]. However,
in case the aggregated responsive demand is significant in proportion to

the total demand, the effect of the response should be considered as well. In many cases found in the literature, the cost is simply assumed to increase quadratically w.r.t. the total load, which can approximate e.g. rising fuel costs [114–116].

2.3 Optimization

2.3.1 The actors

In the smart grid context, there are multiple actors who have different objectives that they attempt to optimize [44]. The main actors in the current electrical grid can for example be categorized [13, 117] to consist of

- electricity generation,

- transmission system operator (TSO),

- distribution system operator (DSO),

- retailers,

- consumers

- and aggregators.

They all have their own objectives ranging from maintaining the grid operation to minimizing costs, which can be achieved through the various markets detailed in Section 2.2.

Electricity generators plan their production schedules and aim to maximize their profits on i.a. the day-ahead markets, while satisfying their ramping and environmental constraints [13]. The TSO[1] (e.g. Fingrid in Finland) aims to maintain the power balance of the transmission grid by determining appropriate balancing power and reserves to contract from the grid participants. The amount of balancing power and reserves have to be optimized by the TSO based on forecasts of the upcoming grid condition and bottlenecks, while their prices are then resolved via market mechanisms. Then the distribution system operators manage the distribution network and communicate the realized consumption back to the suppliers [117]. The retailers[2] (e.g. Fortum in Finland) act on behalf of

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[1] http://www.nordpoolspot.com/How-does-it-work/Transmission-system-operators-TSOs/
[2] http://tem.fi/en/electricity-market

most of the consumers on the electricity markets and try to optimize the purchase of electricity from the markets and selling to the consumers, while offering the consumers electricity at a competitive rate. With responsive consumption, the retailers could act as DR aggregators and simultaneously optimize participation in more dynamic markets such as the markets for balancing and reserves. The consumers can then minimize their electricity costs, while maintaining their level of comfort through the operation of their appliances.

In the research carried out for this thesis, the focus is on the dynamics between an aggregating retailer (i.e. aggregator) and its consumers, while they operate on various markets with their aggregated DR. The optimization involves devising day-ahead plans for several markets, as well as hourly changes to the consumption schedules during the day. In order to achieve the market participation, the aggregator can motivate the consumers either using the price based or incentive based programs. When using the price based approach, the aggregator has to be able to estimate the consumer reaction to the dynamic prices, or alternatively devise an iterative scheme where the prices and thus consumption schedules converge suitably. Conversely, with direct control methods, the aggregator has to centrally manage the optimization and operation of the consumer appliances. The chosen approach has ramifications on the privacy required technical implementation [76, 77], as well as potentially in the amount of flexibility that can be achieved from the consumption [2, 60]. Proposed methods with these different approaches that were found in current state of the art literature are reviewed in the following sections.

One approach to modelling the different actors and their interaction within a smart grid, is to use an agent-based model. The agents can be defined as autonomous actors in the system pursuing their own agenda, while sensing the state of the environment and then acting meaningfully [53]. The low-level interaction between the agents can then result in complex behaviour without explicit models [118]. In multi-agent systems, the agents can also communicate with each other in order to achieve a larger objective [119]. Agent-based modelling and simulation (ABMS) has been used in the smart grid context e.g. for evaluating the impact of deregulation on markets [120], controlling the voltage of the grid [121], and forecasting energy demand [23].

2.3.2   Optimization in general

Constrained optimization problems [122] can be presented in the canonical form

$$\min_{\boldsymbol{x}} g(\boldsymbol{x}) \tag{2.1}$$
$$\text{s.t. } \boldsymbol{x} \in \mathbb{X},$$

where $g(\boldsymbol{x})$ is the objective function that is in this case minimized subject to the defined constraints. $\boldsymbol{x}$ is a vector containing the decision variables and $\mathbb{X}$ defines the set of constraints that describe the values that the decision variables should be limited within in order to maintain a sufficient level of comfort.

The decision variables could simply contain the electricity consumption schedules with an appropriate time step [104, 123, 124]. The electricity demand that could be shifted could then consist of different sources within households, such as various momentarily deferrable appliances, heating with a thermal model for the demand [123] or energy storage charging. For simplification, the demand for electricity could also be modelled using simplistic utility functions [116, 125–127]. The utility functions describe the leveling amount of utility a consumer would achieve from increased electricity consumption, or conversely the disutility of decreasing consumption. However, the payback effect is harder to model with utility functions.

In case the demand is modelled in a more precise fashion, the set of constraints could consist of purely linear equations describing e.g. the storage level of an energy storage and maximum charging levels [124, 128]. Scheduling of appliances other than storages could also be considered and constrained by taking into account their required operation durations and deadlines [59]. With energy management devices, the level of comfort, such as the measured temperature with HVAC loads and water heaters [9, 103, 123], is accounted for in the constraints. For example, the heating energy requirements of a storage space heater could be modelled using a simple energy sink and an energy storage which has to have a sufficient amount of heat energy at all times. One form of linear constraints for

modelling the requirements were proposed by Ali *et al.* [123, 128]

$$0 \leq P_{n,t} \leq P_{max,n} \tag{2.2}$$

$$\sum_{k=1}^{t}(P_{n,k} - Q_{n,k})\Delta t \geq -C_{n,0} \tag{2.3}$$

$$\sum_{k=1}^{t}(P_{n,k} - Q_{n,k})\Delta t \leq C_{max,n} - C_{n,0} \quad \forall \, t \in \{1, \ldots, H\} \tag{2.4}$$

where the storage charging rate $P_{n,t}$ (kW) of consumer n at time t is limited by the maximum rate $P_{max,n}$, storage characteristics (initial charge $C_{n,0}$ (kWh) and maximum capacity $C_{max,n}$ (kWh)) and the hourly heating demand $Q_{n,t}$ (kW). Δt denotes the time step of the optimization and H the optimization horizon (in hours).

The composition of the objective function depends on the actor and its goals. The TSO aims at maintaining the balance of power while preventing i.a. congestion at transmission level, while the DSO prevents congestion distribution levels [101, 129] and minimizes power losses [130, 131]. From the overall perspective, scheduling of production and demand response could consist of e.g. minimizing peak-to-average ratio of consumption [132–134] in order to ease dimensioning of production requirements or minimizing the fuel costs [114–116] resulting in approximately quadratic costs.

For the considered actors in this thesis, the aim is to optimize monetary targets relating to various markets, subject to constraints of these markets and the actor's own operation. In the objective function, costs are included for the periods that are considered in the current decision. In deciding the day-ahead plans for appropriate daily markets, this chosen optimization horizon should extend to at least 24 hours [104, 110, 128]. Then during the day the optimizations could be run again in order to account for realized values in market prices and demand. With a rolling horizon approach the optimization can then be rerun e.g. hourly [101, 135] to account for uncertainties in predictions. However, with a rolling horizon approach, when the optimization have to be run often, the convergence times are of importance. Optimization methods with more predictable convergence are thus often used. In nonlinear approaches, an initial value for iteration can be often constructed from the previously time step. In addition, the requirement might not be to reach the exact optimum value and a "good enough" local minimum can be acceptable.

In case the costs and constraints are linear, the resulting optimization problem is a linear programming problem, which can be solved us-

ing a large choice of off-the-shelf solvers [122]. Different choices in the developed models could introduce quadratic and integer constraints or quadratic costs [104]. The resulting models are then referred to as mixed integer linear programs (MILP) or quadratic programs (QP). However, solving these more complex models is feasible using modern computational capacity [136]. Uncertainties in prices and demand can be included in the problem formulation using e.g. stochastic programming. In stochastic programming, uncertainties in realized market prices and electricity demand are considered in the costs and constraints of the problem [55]. In order to obtain a tractable problem, sample average approximation (SAA) is often used to infuse discrete realizations from the probability distributions of the uncertain components into the problem [55]. The alternative is to simply utilize the expected values of the uncertain components (in contrast to multiple scenarios) to formulate an expected value problem (EVP). The uncertainties could also be included in the constraints of the problem with chance constraints [137], where the problem is defined such that the constraints are satisfied with some probability. Alternatively, the uncertainties could be accounted for by using robust methods that consider worst possible realizations of the costs [114, 138, 139].

In addition to solving convex optimization problems with traditional methods, the considered problems could involve complications such as nonlinearities. Solvers for nonlinear programming problems exist as well but they suffer from problems with increased complexity and local minima [140]. Computational intelligence methods such as particle swarm optimization, neural networks, fuzzy logic and genetic algorithms have also been utilized to model and solve complex and occasionally nonlinear problems in the smart grid context [134, 141, 142].

2.3.3 Aggregation and disaggregation

The level of detail that is to be included in the models is a "fundamental consideration for applying any specific mathematical model", according to Rogers *et al.* [143]. Especially the optimization problems in demand response applications increase in complexity quickly when considering large timescales and the vast number potentially participating appliances. Model aggregation is the method of reducing the problem to a smaller model [143]. Model aggregation can be employed to reduce the computational complexity of the problem by e.g. representing aggregate responses with respect to dynamic prices, in contrast to combining indi-

vidual appliance level subproblems into a larger combined model. The original problem can then be solved by disaggregating the aggregated solution depending on the method used for reducing the problem [143].

Alternatively, the increased computational burden can also be mitigated by decomposing the problem into smaller subproblems that can be concurrently optimized possibly through e.g. iterative methods. Furthermore, in case the consumers individually optimize their consumption w.r.t. given monetary signals, the problem can be approached using *game theory* in order to guarantee that the resulting amount of consumption and incentives are fairly distributed, in case all participants act rationally [144].

Centralized approaches

In case the assumption is made that the aggregator has direct control over the consumer appliances, the optimization could directly consist of solving a combined optimization problem, simultaneously scheduling the consumption of all the individual the devices and then including the monetary benefits in the electricity price of the consumers. A centrally managed optimization approach could be considered e.g. with the target of minimizing power losses [130]. Conversely, costs of energy have been considered in scheduling electric vehicle charging with a centralized controller [145, 146]. Centralized approaches have also been utilized [146, 147] in order to optimize aggregate bids to day-ahead and real-time electricity markets. When market participation is considered for the aggregator, the cost function could comprise of elements such as

- day-ahead market costs [21, 145–149],

- balancing market costs [21, 146, 147, 149],

- real-time market profit [146, 147],

- reserve market participation profit [148],

- energy storage degradation costs [145, 148],

- amount of risks in market operation [21],

- costs of paying incentives to consumers for their shifted load [21],

- operating costs of any owned power plans [147]

- and the costs of demand response infrastructure.

In considering the uncertainties in the markets as well as e.g. demand, sample average approximation (SAA) with stochastic programming solutions have been widely utilized [21, 147, 150]. Alternatively, robust formulations of the problem have also been devised with a centralized aggregator-driven optimization [114, 138, 139]. However, in many parts of the surveyed literature, the focus has also been largely on just solving the optimization problems of the consumers under dynamic prices and other incentives [128, 151, 152].

Game-theoretic approaches

Game theory can be utilized to set the incentives of independently optimizing actors in demand response aggregation, in order to achieve a desired equilibrium. In case the chosen approach involves an aggregator choosing a dynamic price to charge from the consumers, the resulting situation can be described as a *Stackelberg competition* [153]. In an economic Stackelberg leadership model, a lead actor makes its move in the competition first and then the followers move sequentially. The followers are assumed to observe the leader's actions and react in an optimal way, which the leader can anticipate beforehand. In the smart grid context, the aggregator chooses a dynamic price for the consumers, while the consumers change their consumption in order to minimize their electricity costs. The resulting bi-level optimization problem as a whole can be written as

$$\min_{\boldsymbol{y}} \; g(\boldsymbol{y}, \boldsymbol{x}) \tag{2.5}$$
$$\text{s.t. } \boldsymbol{y} \in \mathbb{Y}$$
$$\boldsymbol{x}_n = \arg \min_{\boldsymbol{x}_n} \; g_n(\boldsymbol{x}_n, \boldsymbol{y}) \quad \text{s.t. } \boldsymbol{x}_n \in \mathbb{X}_n \qquad \forall \, n \in \{1, \ldots, N\}$$

where decision variables $\boldsymbol{y}$ of the aggregator depict the prices that are to be optimized, while the consumers $n \in \{1, \ldots, N\}$ optimize their consumption (i.e. decision variables $\boldsymbol{x}_n$) w.r.t. the prices. $\mathbb{Y}$ denotes the set of constraints that the prices are limited to and $\boldsymbol{x}$ the combined set of consumer decision variables. The aggregator tries to minimize its costs of operating in the markets, while maximizing revenue from the consumers given the constraints. The consumers minimize their electricity costs, which the aggregator has to anticipate within its solution.

In particular, Zugno *et al.* [149] proposed a Stackelberg game model in order for an aggregator to achieve load shifting, where the aggregator is assumed to have three models of the consumer optimization behavior de-

scribing different consumer types. The consumers consist of a group of residential houses with flexible heating demand, which they are willing to partly curtail at some price. The bi-level problem is then solved by the aggregator by replacing the second level problems with their equivalent equilibrium constraints. The problem is then defined as a single-level MILP formulation and solved using an off-the-shelf solver. In other Stackelberg approaches, the consumer-level demand in has also been modelled using utility functions [125, 127] and by estimating the cross-elasticity between different hours [154].

Distributed approaches

In order to solve a large-scale demand response optimization problem with a large number of participating consumers and appliances, the optimization could potentially be reformulated to be distributed to the level of single consumers or appliances. In addition to helping the computational tractability of the problem, decomposing the problem would protect some of the privacy of the consumer-level constraints, such as relating to their level of comfort. However, if the optimization is decomposed w.r.t. the consumers, the difficulty of solving the aggregate problem is increased by any *complicating constraints*, such as those which involve the aggregate schedule. An aggregate optimization problem that can be decomposed could take the form of

$$\min_{\boldsymbol{x}} \sum_{n=1}^{N} g_n(\boldsymbol{x}_n) \tag{2.6}$$
$$\text{s.t.} \sum_{n=1}^{N} A_n \boldsymbol{x}_n = \boldsymbol{b}$$
$$\boldsymbol{x}_n \in \mathbb{X}_n \quad \forall\, n \in \{1, \ldots, N\}$$

where the matrices A_n and vector $\boldsymbol{b}$ describe the complicating constraints that involve schedules from different consumers. The coordination of the complicating constraints could be aided by using the Lagrangian formulation, where the dual variables of the decision variables represent additional costs and compensations of violations in the given constraints [122]. With linear problems, quadratic terms can be included to assist in the convergence of iterating for the optimal variables, resulting in for example the alternating direction method of multipliers (ADMM) [155]. Consequently, ADMM has been widely utilized in research involving the scheduling of various loads, when complicating constraints are involved. For example, electric vehicle charging has been coordinated with ADMM

for the purposes of valley-filling [156], cost minimization [157], and network [158] and charging station capacity compliance [159]. The parallel iteration of the distributed optimization can be facilitated with e.g. a Jacobi-Proximal variation [160], which includes additional regularization terms.

2.4 Practical applications

In practice, several energy storage applications exist that are used in balancing the grid. In the production side, e.g. pumped hydrothermal plants use their hydraulic potential energy to decrease peak load and provide frequency regulation [161]. Furthermore, wind power generation is currently tested in conjunction with heat storages [162] and batteries [163] in order to refrain from having to curtail production during periods of high production and low demand. Pilot installations of large stand-alone battery energy storage systems (BESS) have also been introduced to provide various grid maintenance operations including frequency regulation [164–166].

Demand response with the charging of electric vehicles [167–169] and dedicated batteries [170] have also been tested in some pilot projects. However, many consumer-level demand response pilot projects have been limited to curtailing peak consumption [171, 172] or relying on active participation of consumers without automated control [25, 26]. Several pilot programs involving frequency control have also been carried out [32, 173]. Currently available commercial applications of residential demand response range from companies offering thermostats mainly for obtaining energy efficiency and price responsiveness [174–177], as well as some aggregators focusing on larger industrial customers offering responses to grid reliability events [178]. For residential consumers the options offered by aggregators are typically energy savings, dynamic pricing and reliability event participation [178]. However, aggregation for more continuous grid services such as reserve participation is envisioned as a potential next step [170].

3. Results

This chapter summarizes the results achieved in this thesis. At first, the general model structure characterizing the objectives, costs and constraints of the relevant actors, is described. Results from the performed simulations are first presented from the publications focused on planning day-ahead consumption schedules and achieving intra-day flexibility (PI–II). Then, results are presented for the research conducted for the purposes of utilizing this flexibility for frequency control (PIII–VI). During the presented optimization formulations, the notation might differ slightly from the original publications in order to maintain consistency within the thesis.

3.1 System model

In much of the research aiming at making use of demand response, an aggregating entity is assumed to act as an intermediary between the markets and consumers [19]. In the work presented in this thesis, the focus is on the role of the aggregator and its consumers, with respect to the markets. The aggregator aims to utilize the flexibility of its consumers in various markets, while the effects on the level of comfort of the consumers are minimized. In the following, several different approaches are considered for controlling the consumption. The electrical loads of the consumers could be directly controllable by the aggregator, or alternatively the aggregator might only have more indirect ways to influence the consumption through e.g. pricing of electricity or bidding methods. Agent-based modelling is featured in some of the publications, with a hierarchical control structure for the considered actors. However, in all the presented publications, the actors maintain some level of control over their actions.

Figure 3.1 portrays the relevant actors that are involved in the follow-

ing studies and their hierarchical structure. The aggregator acts on the markets operated by the TSO and Nord Pool, while predicting the effects of other consumption, grid frequency and external temperatures on its aggregate consumption and potential costs. In the following, the consumers are generally assumed to have some type of energy storage and thermal energy consumption. The external effects that are studied in this thesis include other inflexible electricity consumption that the aggregator might have in addition to its responsive consumers, the dynamics of the electrical grid, and market behaviour. In addition, the thermal energy demand is dictated largely by the local outside temperatures in conjunction with the the thermal dynamics and level of comfort requirements of the occupants.
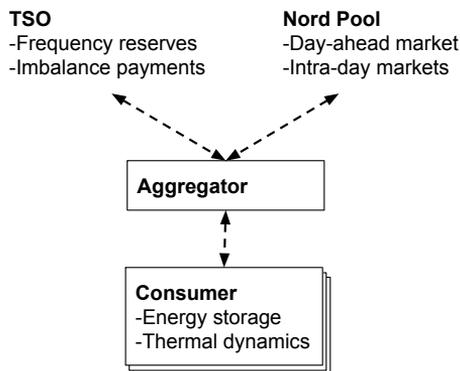
Figure 3.1. The relevant actors in the considered smart grid and their interactions.

Costs

The markets where the aggregator attempts to utilize its aggregated DR have different operational timescales and requirements. In particular, the markets that have been considered in the presented publications include

- Day-ahead wholesale market [111]

- Intra-day [106, 179]

- Frequency controlled reserves [108]

Table 3.1 illustrates the extent that the different markets are involved in the publications. In the included table, the effect of possible balancing costs of the aggregator are also included as intra-day market involvement. In addition, the intra-day markets in the breakdown table include

the Elbas and balancing market. The frequency reserves consideration is counted also for the publications where the market participation is not directly considered, but instead the more technical implementation concerns are researched (i.e. PIII). At first, the focus is on attaining intra-day flexibility from day-ahead plans, and then on applying flexibility to frequency control. The costs of the consumers include the taxes and grid tariffs as static costs. The grid tariffs are assumed as constant over the considered simulations and as only shifting of consumption is mainly considered, the total costs is not affected by the demand response actions.

Table 3.1. The included markets and timescales dealt within different publications.

| Market(s) \ Publication	I	II	III	IV	V	VI
Day-ahead market	✓	✓		✓	✓	✓
Intra-day markets	✓	✓		✓		✓
Frequency controlled reserves			✓	✓	✓	✓

To account for the different timescales of the markets, in some publications stochastic optimization models with multiple stages are developed to solve the studied problems. During the first stage, decisions on the consumption schedule to purchase from the day-ahead market have to be fixed, before the market prices and actual electricity demand are known. Then, the daily reserve market commitments have to be made. During the operating day, the electricity demand is evaluated and intra-day decisions are made based on the chosen markets, and reserves. In some of the developed models, only certain parts of the markets are included, or even completely excluded. The electricity prices used in the simulations are the real values obtained from Nord Pool[1], for years ranging from 2013 to 2015. During the optimization, the aggregator is assumed to be able to forecast the day-ahead prices with an accuracy where the mean square error (MSE) is in the order of 6 €/kWh^2 [112]. The price scenarios (i.e. forecasts) are generated with a multivariate Gaussian process [149] from the actual prices. Corresponding realized values are also used for the balancing and intra-day market prices. Meanwhile, the frequency reserve prices are forecasted using an ARMAX (autoregressive moving average with exogenous variables) model, which is then used to also generate scenarios for the stochastic programming formulation.

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[1] http://www.nordpoolspot.com/historical-market-data/

Consumption models

The consumers are modelled as residential houses with an energy storage for temporarily storing energy in either heat or electrical form. The general model that is considered is illustrated in Figure 3.2, where the charging, discharging and electricity demand constrain the state of charge of the storage. The discharging of the storage means in the context of the thesis the utilization of the energy in the storage within the house, either directly in the form of heat or as using other electric heating devices. The demand of the house is consequently formed by the external temperature, level of comfort requirements of the residents and thermal properties of the building. An energy storage is included with its state of charge (SOC), either in the form of e.g. a water tank for heating or an electric battery system.

For simplification, the house demand can be modelled as a dynamic energy sink where the heating is generated directly from the electricity from the grid or from a storage, e.g. when the heating is provided by electric storage space heaters [35, 128], or a battery in conjunction with a heat pump. Only the heating demand is considered and other consumption sources are ignored in the simulations, and thus the load curve is simply the heating demand of the individual houses. The hourly heating demand is simulated from a house model and ambient temperatures. The house dynamics were modelled in more detail using a two capacitance model [123] to more accurately capture the hourly heating demand. The model includes parameters for the thermal capacities of the indoor temperature and house structures, thermal conductances, external temperature and ventilation supply temperature. The houses in the simulations were generated from the aforementioned models by varying all the parameters by 20%. A suitable number of houses, based on the complexity and number of simulated scenarios, were then generated and in some publications the resulting consumption schedules were scaled in order to achieve grid-scale responses. Furthermore, in several of the publications, the aggregator is assumed to have under its contract also other consumers that do not react to prices. This inflexible consumption is generated again with a Gaussian process.
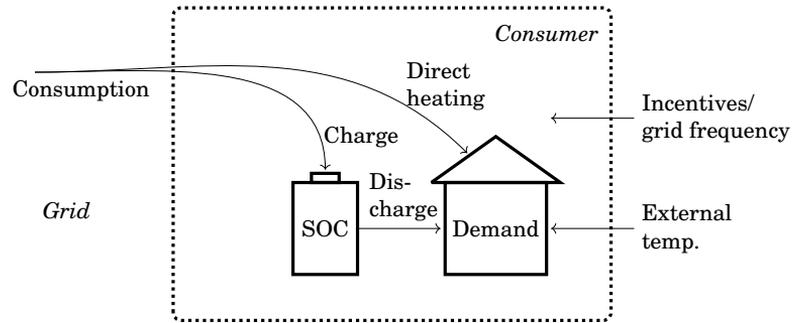
Figure 3.2. An illustration of the model of the studied consumers.

Demand response can then be offered from the charging and direct heating schedules, as long as the stated constraints can be held for the following hours. For offering the DR, the costs of potential subsequent rescheduling that could be required, might have to be considered, especially when the consumers operate independently. In particular for reserve operation, care has to be made in being able to deliver the promised reserve capacities to their full extent.

3.2   Optimizing day-ahead consumption plans and rescheduling

In the research presented in this section, the focus is on obtaining flexibility from mainly independently acting residential houses for planning day-ahead schedules for energy market acquisition (PI). Then the intraday flexibility in the planned schedules is investigated using several approaches (PII).

3.2.1   Optimizing dynamic prices

The framework in Publication I presents a method for determining the day-ahead dynamic electricity price that an aggregating retailer should charge from its consumers, in order to get a desired demand profile. The consumers optimize independently with respect to the price and the aggregator estimates their reactions to the price changes via approximate models. Similarly to the work by Zugno *et al.* [149], a Stackelberg formulation is proposed, however the proposed new model is now solved using a genetic algorithm. Due to the nonlinearities in the objective function, a genetic algorithm was chosen. Furthermore, obtaining the optimimum solution is not strictly necessary and a compromise is already made in using the stochastic scenario approach. In addition, optimization of dis-

counts for obtaining further flexibility from the schedules was considered, in order to minimize aggregate imbalances between the purchased and realized consumption schedules.

Proposed model

With regards to the studied markets, the day-ahead wholesale market and hourly intra-day markets were considered, while the consumers were modelled as simple energy sinks with an expected demand and an energy storage. In particular, the application could be a storage space heater with the purpose of providing heating in colder climates [128]. In the proposed bi-level optimization model, an aggregator has a group of independently optimizing consumers as well as a number of inflexible loads. The inflexible load consists of the unpredictable consumption that the aggregator can not affect and could thus result in imbalance costs. In total, the daily costs that the aggregator aims to minimize by varying the consumer price consist of electricity acquisition costs and imbalance costs. The price which the aggregator can charge from the consumers is limited by the assumed contract to the same mean, minimum and maximum values as the market price. The stochastic program is defined in full as

$$\min_{P_t^{\omega_1}, K_t^{\omega_1}} \frac{1}{\Omega \cdot \Omega} \sum_{t=1}^{H} \sum_{\omega_1=1}^{\Omega} \sum_{\omega_2=1}^{\Omega} \left(K_{s,t}^{\omega_1} E_t - K_t (P_t^{\omega_1} + \delta L_t^{\omega_1,\omega_2}) \right.$$

$$\left. + \pi_{\uparrow,t}^{\omega_1,\omega_2} \Delta E_{\uparrow,t}^{\omega_1,\omega_2} + \pi_{\downarrow,t}^{\omega_1,\omega_2} \Delta E_{\downarrow,t}^{\omega_1,\omega_2} \right) \Delta t \quad (3.1)$$

$$\text{s.t. } P_{n,t}^{\omega_1} = \arg \min_{P_{n,t}^{\omega_1}} \sum_{t=1}^{H} (K_t^{\omega_1} P_{n,t}^{\omega_1}) \Delta t \quad (3.2)$$

$$0 \le P_{n,t} \le P_{max,n} \quad (3.3)$$

$$\sum_{k=1}^{t} (P_{n,k} - Q_{n,k}) \Delta t \ge -C_{n,0} \quad (3.4)$$

$$\sum_{k=1}^{t} (P_{n,k} - Q_{n,k}) \Delta t \le C_{max,n} - C_{n,0} \quad \forall\, t \in \{1, \dots, H\} \quad (3.5)$$

$$P_t^{\omega_1} = \sum_{n=1}^{N} P_{n,t}^{\omega_1} \quad (3.6)$$

$$E_t = \frac{1}{\Omega \cdot \Omega} \sum_{\omega_1=1}^{\Omega} \sum_{\omega_2=1}^{\Omega} \left(P_t^{\omega_1} + \delta L_t^{\omega_1,\omega_2} \right) \quad (3.7)$$

$$\Delta E_{\uparrow,t}^{\omega_1,\omega_2} = \begin{cases} -\Delta E_t^{\omega_1,\omega_2} & \text{if } \Delta E_t^{\omega_1,\omega_2} < 0 \\ 0 & \text{else} \end{cases} \quad (3.8)$$

$$\Delta E_{\downarrow,t}^{\omega_1,\omega_2} = \begin{cases} \Delta E_t^{\omega_1,\omega_2} & \text{if } \Delta E_t^{\omega_1,\omega_2} > 0 \\ 0 & \text{else} \end{cases} \quad (3.9)$$

$$\Delta E_t^{\omega_1,\omega_2} = E_t^{\omega_1} - \left(P_t^{\omega_1} + \delta L_t^{\omega_1,\omega_2} \right) \quad (3.10)$$

$$K_{min} \le K_t^{\omega_1} \le K_{max} \quad (3.11)$$

$$\frac{1}{H} \sum_{t=1}^{H} K_t = \bar{K} \qquad \forall\, n, t, \omega_1, \omega_2 \quad (3.12)$$

where the bi-level optimization consists of the aggregator minimizing its purchase and balancing costs (3.1), while the actual consumption results from the consumers minimizing their own costs (3.2). The constraints (3.3)–(3.5) define the limits on the charging rate such that the level of comfort is not affected [123, 128], and the constraints (3.6) and (3.7) define the aggregate realized consumption of the controllable consumers and the total expected consumption respectively. Constraints (3.8)–(3.10) then define the positive and negative imbalances between the purchased and realized consumption. Finally, constraints (3.11)–(3.12) denote the constraints that the aggregator has to obey when deciding the day-ahead price to charge from the consumers.

In the objectives and constraints E_t (kW) denotes the amount of hourly

energy to purchase from the day-ahead market, while $K_{s,t}^{\omega_1}$ (€/kWh) are the day-ahead market price scenarios, and K_{min}, K_{max} and $\bar{K}$ the limits on the price. $\delta L_t^{\omega_1,\omega_2}$ (kW) are the realized scenarios of inflexible consumption, resulting in imbalances $\Delta E_t^{\omega_1,\omega_2}$ (kW) that have to be compensated with the balancing prices $\pi_{\uparrow,t}^{\omega_1,\omega_2}$ and $\pi_{\downarrow,t}^{\omega_1,\omega_2}$ (€/kWh). The decision variables are the prices K_t (€/kWh) to charge from the consumers and the consumption schedules $P_{n,t}^{\omega_1}$ (kW).

The stages represented by the superscripts ω_1 and ω_2 describe the variables that are *revealed* (i.a. the prices $K_{s,t}^{\omega_1}$) or have to be decided (i.a. the consumption $P_{n,t}^{\omega_1}$) after the respective stages. The first stage scenarios ω_1 denote the uncertain prices of the day-ahead market and the consumption schedules that the consumers then choose based on the prices. The second stage ω_2 then denotes the uncertain realized demand and balancing market costs. For example, the imbalances $\Delta E_{\uparrow,t}^{\omega_1,\omega_2}$ are dependent on the realizations of values in both the first and second stages. Multiple scenarios Ω are utilized in both stages to account for different possible realizations of the prices and consumption.

The optimization problem is then solved by the aggregator with a genetic algorithm [180], where the lower-level problem (3.2)–(3.5) is solved by an LP solver. The genetic algorithm was initialized with a population of 200 price vectors that satisfy the constraints. The fitness scaling function is proportional to $1/\sqrt{i}$ for individual with rank i. Stochastic uniform selection is used, and for reproduction 10 price vectors are chosen unchanged and 160 vectors are chosen for crossover. A maximum of 5000 generations are optimized. The consumers in the aggregator formulation consist of three approximate models that describe the aggregate behaviour of the consumers. The approximate models are similar to the aforementioned model (3.1)–(3.12) but with appropriately scaled consumption and parameters identified by e.g. detecting suitable groups within the behaviour and characteristics of the consumers. Then during the day a larger group of actual simulated consumers optimize hourly w.r.t. their demand and prices.

In addition, during the day discounts are optimized by searching for a suitable size for the discount and number of consumers to give the discount to, for the current hour (in case of need for increase) or the following hour (in case of need for decrease in consumption). The discount is

optimized by solving

$$\max_{\Delta K, \mu} \pi_t (\Delta E_t + P_t^d - P_t)\Delta t + \sum_{k=t}^{H} \mu(K_k^d P_k^d - K_k P_k)\Delta t \qquad (3.13)$$

subject to the same constraints as in the previous day-ahead optimization. The benefits are maximized by solving an appropriate amount of discount ΔK (€/kWh) for a some percentage μ of consumers. K_k is the realized price that is charged from the consumers that has been optimized in the day-ahead optimization, while K_k^d is the price with a discount (ΔK) for the current hour ($k = t$) if the aim is to increase consumption and for a following hour ($k = t + 1$) if the aim is to reduce consumption. The DR obtained from the discounts was used to avoid imbalance payments, as well as for providing power in the intra-day balancing market [106] (contained in the payment π_t).

Results

20 days with differing market price and inflexible load scenarios were optimized and simulated with 300 consumers. The solutions for the second-level linear programs were obtained in the order of seconds, while solutions to the first level were obtained by the off-the-shelf genetic algorithm solver in Matlab. Price and weather data was used from the winter of 2013 from Helsinki, Finland. Figure 3.3 displays the resulting consumption profiles as well as the remaining imbalances. The first subfigure shows in the controlled storage heater population and with a dashed line the inflexible consumption that results in the forecast imbalances. The shaded areas depict the uncertainties in the consumption profiles resulting from possible variations in i.a. external temperatures. In the second subfigure, the remaining imbalances after the operating hours are shown, with vertical lines indicating the hours where discounts have been optimized and given to consumers. It can be seen that for the hours with discounts, the amount of remaining imbalances was minimal, suggesting that the small discounts were able to reduce imbalance payments, by reducing or increasing consumption when needed.
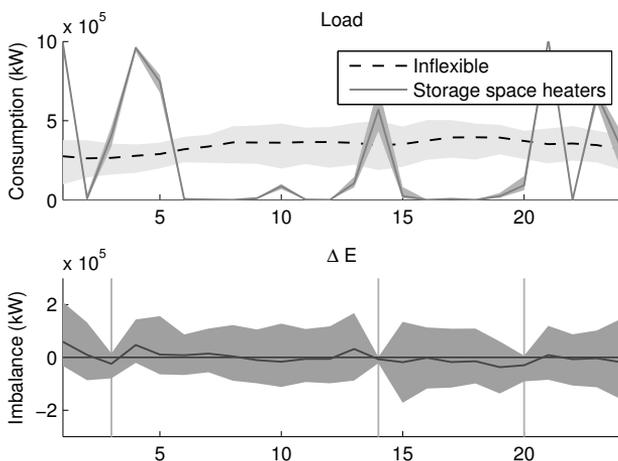
Figure 3.3. The realized consumption of the storage space heaters and inflexible loads charged with the optimized dynamic price and additional discounts at the indicated locations and the imbalance power; including the 90% percentiles from the various scenarios simulated. (PI)

The numerical results (Publication I) on the costs and profits indicated that the dynamic pricing offered slightly smaller and more predictable costs, especially for the aggregator. The developed dynamic pricing optimization was also compared to cases where the consumers were directly charged the market price and similarly constrained static TOU prices.

The uncertainty in the day-ahead market prices resulted in large volatility of the consumption profiles, and resulting imbalance costs in all considered test scenarios. However, the optimized pricing in conjunction with the discounts was found to be able to reduce average imbalances and their costs.

3.2.2 Comparing incentives for control

An aggregator has several alternative approaches for shaping its aggregate consumption profile, depending on how directly the aggregator can control the consuming appliances. In the following publication (PII), the aim was to compare several alternative strategies that an aggregator has in controlling the consumption profiles of its customers, with various uncertainties taken into account. The more concrete aim was to firstly examine the amount of intra-day DR and the resulting profit that could be obtained from consumers that planned their storage charging w.r.t. the day-ahead electricity price. The secondary objective was to improve upon the achievable DR in the case where the aggregator has more direct con-

trol over the loads.

Proposed models

For comparing the amount of flexibility, the problem is again formulated as a stochastic programming problem, where the aggregator first plans the energy acquisition when there are uncertainties in the day-ahead prices, and then in the second stage takes into account intra-day costs with uncertainties in the inflexible consumption. The considered consumers consist again of energy sinks with energy storages and an uncertain amount of energy demand. The level of comfort of the consumers is in this instance maintained by providing the required demand with some certainty. The cost and profit sources consist of the day-ahead market and the imbalance costs, as well as the profits that the aggregator can achieve in the intra-day trading market.

Several cases were devised for examining the amount of control that could be achieved under different assumptions. The aim was to compare the amount of intra-day DR between a case where the consumers independently minimize their costs with respect to the day-ahead price, and a case where the aggregator can directly schedule the consumer loads and anticipate the potential need for DR. At first, a common form of contract[2,3] where the consumers are charged the spot price plus a margin for their electricity and then can independently minimize their costs, is considered. Then, the aggregator aims to further affect their consumption through monetary incentives, to which the consumers react to if they benefit from the transaction without affecting their level of comfort. An alternative case considers a contract where the aggregator has direct load control (DLC) over the loads of the consumers. In the more direct control approaches the aggregator can then more freely plan the charging schedules of the consumer energy storages. In both approaches it is assumed that the consumers are obliged to report their consumption plans to the aggregator. The cases that have been devised for examining the controllability differences consist of

- *RTP* where the consumers are charged the day-ahead market price and the aggregator purchases the expected consumption profile from the day-ahead market.

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[2] https://www.vantaanenergia.fi/en/products/spot-energy/

[3] https://www.fortum.com/countries/fi/sahko/sahkosopimus/tarkka-sopimus/pages/default.aspx

- *DLC* where the consumers are charged a flat rate and directly controlled to set their day-ahead consumption plans so that the profiles minimize costs with respect to the expected day-ahead price.

- *DLC opt.I* where a flat rate is again assumed and in the day-ahead optimization the aggregator takes into account the potential intraday rescheduling benefits and costs from compensations to consumers.

- *DLC opt.II* where the aggregator has even more complete control and is not required to take into account consumer rescheduling costs beforehand.

In the RTP case, the consumers independently optimize their consumption, and before the operating day share with the aggregator their potential schedules for various price forecasts. Then during the day the aggregator requests from the consumers the prices at which they would be willing to change their optimized consumption. Conversely, in the DLC cases, the consumers are charged a flat rate and the aggregator directly controls the consumption, but either directly compensates the consumers for their changed consumption profiles (in the DLC and DLC opt.I cases) or through a lower flat electricity price (DLC opt.II case).

RTP case

In the RTP case, before the operating day the consumers forecast their consumption schedules with respect to various price scenarios by solving

$$\min_{P_{n,t}^{\omega_1}} \sum_{t=1}^{H} \left(P_{n,t}^{\omega_1} K_{s,t}^{\omega_1} \right) \Delta t \tag{3.14}$$

$$\text{s.t. } 0 \leq P_{n,t}^{\omega_1} \leq P_{max,n} \tag{3.15}$$

$$\sum_{k=1}^{t} \left(P_{n,k}^{\omega_1} - Q_{n,k}^{\omega_1} \right) \Delta t + C_{n,0} \geq \sigma_{Q,n} \sqrt{t} \Phi_\epsilon^{-1} \tag{3.16}$$

$$\sum_{k=1}^{t} \left(P_{n,k}^{\omega_1} - Q_{n,k}^{\omega_1} \right) \Delta t + C_{n,0} - C_{max,n} \leq -\sigma_{Q,n} \sqrt{t} \Phi_\epsilon^{-1} \tag{3.17}$$

$$\forall\, t \in \{1, \dots, H\} \tag{3.18}$$

for different price forecasts denoted by the superscripts ω_1. $P_{n,t}^{\omega_1}$ is again the consumption, while $K_{s,t}^{\omega_1}$ is the spot price. The constraints (3.16)–(3.17) limit the state of charge of the energy storage such that there is energy to meet the demand with a $\epsilon = 95\%$ certainty, with the assumption that the forecast errors in the demand are normally distributed

$$Q_{n,t}^{\omega_1,\omega_2} \sim Q_{n,t}^{\omega_1} + \mathcal{N}(0, \sigma_{Q,n}^2).$$

Φ_ϵ^{-1} represents the value of the standard normal inverse cumulative distribution function at percentage ϵ while $\sigma_{Q,n}$ denotes the standard deviation of the forecast errors. The expected (average over considered scenarios) aggregate schedule

$$E_t = \frac{1}{\Omega} \sum_{\omega_1=1}^{\Omega} \sum_{n=1}^{N} P_{n,t}^{\omega_1}$$

is then calculated by the aggregator from these forecasts and purchased from the day-ahead market.

During the day, the consumers again optimize (3.14), but now against the realized prices. Then, the consumers offer hourly bids to the aggregator for what prices they would be willing to shift their consumption. These bids were developed by Alahäivälä (PIV) and then expanded in Publication II for uncertainties in demand. The maximum amount of demand the consumers are willing to increase ($\delta P_{\uparrow,n,t}$) or decrease ($\delta P_{\downarrow,n,t}$) can be determined by

$$\delta P_{\uparrow,n,t} = \min \left(P_{max,n} - P_{n,t}^{\omega_1}, \right.$$
$$\left. C_{max,n} - (C_{n,t-1}^{\omega_1} - Q_{n,t}^{\omega_1} - \sigma_{Q,n}\Phi_\epsilon^{-1}) \right) \qquad (3.19)$$
$$\delta P_{\downarrow,n,t} = \min \left(P_{n,t}^{\omega_1}, \right.$$
$$\left. P_{n,t}^{\omega_1} + C_{n,t-1}^{\omega_1} - Q_{n,t}^{\omega_1} - \sigma_{Q,n}\Phi_\epsilon^{-1} \right) \qquad (3.20)$$

where ω_1 denote the scenarios for the now-realized consumption and prices and $C_{n,t-1}^{\omega_1}$ (kWh) the state of charge of the current hour. The prices for which these potential reductions and increases would be fulfilled, can be evaluated by rerunning the optimization (3.14) with the altered demand and calculating the change in cost (see PIV for details).

DLC case

In the basic DLC case, the aggregator directly schedules the energy storage charging of the consumers, such that simply the individual expected acquisition costs are minimized. The cost function could be written as

$$\min_{P_{n,t}} \frac{1}{\Omega} \sum_{\omega_1=1}^{\Omega} \sum_{n=1}^{N} \sum_{t=1}^{H} \left(P_{n,t} K_{s,t}^{\omega_1} \right) \Delta t \qquad (3.21)$$

$$\text{s.t. } (3.15) - (3.17) \quad \forall \, P_{n,t} \qquad (3.22)$$

The consumers are charged a flat fee and the aggregator is assumed to be able to shift their charging, in case their level of comfort is not affected and proper compensation is again provided. The same bidding algorithm (eqs. (3.19)–(3.20)) is used to calculate the potential amount and costs of the rescheduling, but with a flat rate.

DLC opt.I case

The DLC opt.I case assumes again a flat rate for the consumers and direct control from the aggregator. However, in the optimization, the aim is to take into account the balancing costs resulting from unforeseen imbalances with respect to the purchased schedule, as well as potential regulating market profits. Two stages are considered, where at first the day-ahead plans are considered for different scenarios of market prices (ω_1) and then the imbalances are revealed and reacted to (ω_2). The optimization is then formulated to include a set of inflexible consumption imbalance scenarios $\delta L_t^{\omega_2}$ (kW) and the countering demand response scenarios $\delta P_{n,t}^{\omega_1,\omega_2}$ (kW). The cost minimization is formulated as

$$\min \; \frac{1}{\Omega \cdot \Omega} \sum_{\omega_1=1}^{\Omega} \sum_{\omega_2=1}^{\Omega} \sum_{t=1}^{H} \left(K_{s,t}^{\omega_1} L_t^{\omega_1,\omega_2} + \pi |E_t - L_t^{\omega_1,\omega_2}| + J_t^{\omega_1,\omega_2} \right) \Delta t \quad (3.23)$$

$$\text{s.t. } (3.15) - (3.17) \quad \forall \; P_{n,t}^{\omega_1} \quad (3.24)$$

$$(3.15) - (3.17) \quad \forall \; P_{n,t}^{\omega_1} + \delta P_{n,t}^{\omega_1,\omega_2} \quad (3.25)$$

$$E_t = \frac{1}{\Omega} \sum_{\omega_1=1}^{\Omega} \sum_{n=1}^{N} \left(P_{n,t}^{\omega_1} \right) \quad (3.26)$$

$$L_t^{\omega_1,\omega_2} = \delta L_t^{\omega_2} + \sum_{n=1}^{N} \left(P_{n,t}^{\omega_1} + \delta P_{n,t}^{\omega_1,\omega_2} \right) \quad (3.27)$$

$$J_t^{\omega_1,\omega_2} = \sum_{n=1}^{N} \left(K_{flat} \cdot \delta P_{n,t}^{\omega_1,\omega_2} \right) \Delta t \quad (3.28)$$

$$\sum_{n=1}^{H} \left(P_{n,t}^{\omega_1} \right) \Delta t \leq \sum_{t=1}^{H} \left(Q_{n,t}^{\omega_1} \right) \Delta t - C_{n,0} - \sigma_{Q,n} \sqrt{H} \Phi_\epsilon^{-1} \Delta t \quad (3.29)$$

where the objective (3.23) consists of acquisition costs, balancing costs and compensations over two stages of scenarios. The realized load $L_t^{\omega_1,\omega_2}$ (kW) consists of the day-ahead plans, DR scenarios and imbalances from any inflexible consumption that the aggregator aggregates. π (€/kWh) represents the average imbalance costs and potential compensations from intra-day market, relative to the day-ahead price ($K_{s,t}^{\omega_1} - \pi$ and $K_{s,t}^{\omega_1} + \pi$) The consumer compensation $J_t^{\omega_1,\omega_2}$ (€) consists of the flat rate K_{flat} (€/kWh) that is charged from the consumers and the DR $\delta P_{n,t}^{\omega_1,\omega_2}$ (kW). The constraints (3.24)–(3.25) limit the base charging schedules and charging schedules after potential demand response actions to the storage limits. The last constraint (3.29) then limits the daily consumption so that the energy storage is not charged during the day more than is needed by the

energy demand.

DLC opt.II case

In the DLC opt.II case, the aggregator is again assumed to optimize the schedules for additional DR flexibility, but in this case the aggregator does not have to directly compensate the consumers. Instead, the flat rate is reduced from the basic *DLC* case. The day-ahead optimization then consists of solving the more compact problem of

$$\min \frac{1}{\Omega \cdot \Omega} \sum_{\omega_1=1}^{\Omega} \sum_{\omega_2=1}^{\Omega} \sum_{t=1}^{H} \left(K_{s,t}^{\omega_1} L_t^{\omega_1,\omega_2} + \pi |E_t - L_t^{\omega_1,\omega_2}| \right) \Delta t \qquad (3.30)$$

$$\text{s.t. } (3.24) - (3.27)$$

Case studies and results

The aforementioned cases are studied with optimizations over 140 days with 20 consumers, scaled to correspond to a 1000 houses, in order to achieve market level responses. The market prices are chosen from the beginning of 2015. Figure 3.4 displays the resulting day-ahead profiles of a particular day, where a slightly flatter profile can be seen with the optimized cases. During the operating day, the inflexible imbalances ($\delta L_t^{\omega_2}$) are realized and the imbalances are minimized by the aggregator either by directly controlling the consumption or through the bidding algorithm and compensating accordingly. In addition, any remaining flexibility is simulated to be utilized in the intra-day hourly market [179].
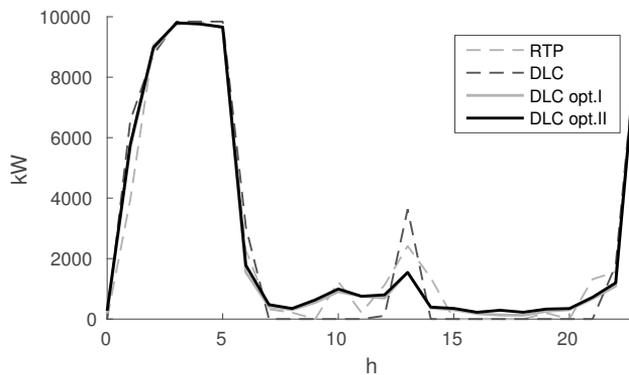
Figure 3.4. The scheduled acquisition profiles for the first day in the optimizations, for the various cases. (PII)

Figure 3.5 displays the weekly costs of the different cases in comparison to the RTP case when intra-day demand response is not utilized (RTP w/o

DR). The total costs indicate that a significant decrease can be achieved by employing the intra-day demand response in all the considered cases. In addition, the more direct control approaches afford more control, resulting in smaller costs, albeit with higher variances. In short, comparing the DLC and RTP cases illustrated the decrease in achievable DR when the consumers consider their own rescheduling costs. The decrease could possibly be countered if the consumers anticipated the potential benefits they could achieve from planning their consumption schedules so that they can provide DR. However, this would increase the complexity of the consumer-side optimization and the amount of information and assumptions the consumers would have to include. The optimized DLC cases highlighted the importance of considering flexibility in the day-ahead planning, however with an increased variance in the costs.
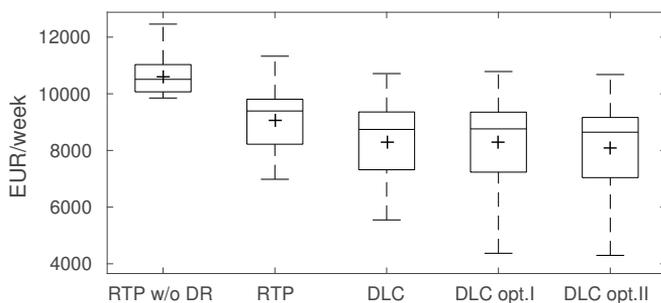
Figure 3.5. The resulting total average social cost (+) and their distributions for the different cases. (PII)

In comparison, Figure 3.6 shows the costs of the consumers with the different contracts. The RTP and DLC costs are not directly comparable due to differences in pricing depending on the margin set by the aggregator in the dynamic and flat rates. The margin has been chosen such that in the uncontrolled case the costs are equivalent. It can be seen how the variance of the costs is higher in the dynamic pricing case and the average costs of the consumers decrease with the inclusion of demand response.
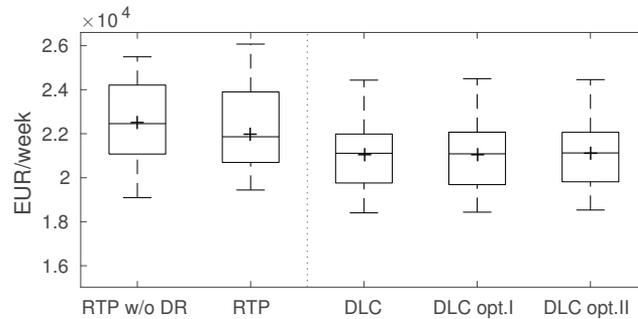
Figure 3.6. The resulting total average costs of the consumers (+) and their distributions for the different cases. (PII)

However, the potential hourly intra-day participation that was included in the day-ahead optimization (in cases DLC opt.I and opt.II) was only considered within a single stage (i.e. in contrast to hourly independent stages), and could be further improved. Furthermore, in the assumed RTP case, the consumers had to be willing to share their potential charging schedules (with respect to several forecasts) before the operating day, which could be avoided by constructing a mechanism for the aggregator with which it forecasts the price responsiveness of the consumers.

3.3 Participation in frequency reserves

This section summarizes the developed models and results obtained in publications III–VI. The contributions in the publications range from results related to achieving and maintaining real-time frequency control under communication constraints, to optimizing day-ahead plans for reserve market participation.

3.3.1 Frequency control

At first, the focus was on attaining and maintaining frequency control using residential houses equipped with heating loads (Publications III and IV). In Publication III the problem of maintaining centralized frequency control under uncertain communication links was studied. The market effects were not yet considered, but instead the aim was to simulate the execution of disturbance reserve (FCR-D) operation during a disconnection of a large power plant. The control signal is centrally transmitted to an appropriate number of houses to enact a suitable change in aggregate consumption. The frequency dynamics are modelled using a simplified

model of the Finnish grid [181], where the fluctuations of the grid frequency deviations Δf_t (1/s) are evaluated in response to changes in the amount of production $\Delta P_{G,t}$ (kW) and consumption $\delta P_{DR,t}$ (kW). The differential equation

$$\frac{2W_k}{f_n}\Delta f'_t + W_v\Delta f_t = \Delta P_{G,t} + \delta P_{DR,t} \tag{3.31}$$

is solved, where W_k and W_v are rotational inertia constants (kWs), f_n (1/s) is the nominal frequency of the grid, and $\Delta f'_t$ (1/s^2) is the derivative of the frequency deviations. In addition, a first-order model was utilized for the thermal dynamics of the houses performing the demand response [182].

In order to simulate the effect of varying communication channels that could be utilized by the aggregator to control the consumers, an agent-based modelling and simulation application was developed. The model consisted of a hierarchical structure with consumer, power plant and VPP agents interacting within the grid. Figure 3.7 depicts a class diagram illustrating the proposed hierarchical model. The consumer and power plant agents are defined as similar electrical devices that interact with the simulated grid, while the VPP agent (the aggregator) instructs the consumers. The decision logic is defined so that the consumer agent monitors its temperature, while obeying orders from the aggregator in case they do not affect its level of comfort. The simulations were carried out using a discrete-event scheduler, which can accurately schedule the stochastic arrivals of the control messages, performing actions by the agents and updating the dynamics of the involved systems such as the temperature models and the grid. The aggregator centrally controls the heating of the houses when it monitors deviations in the grid frequency. The amount of DR that is dispatched is chosen linearly w.r.t. the monitored deviations.
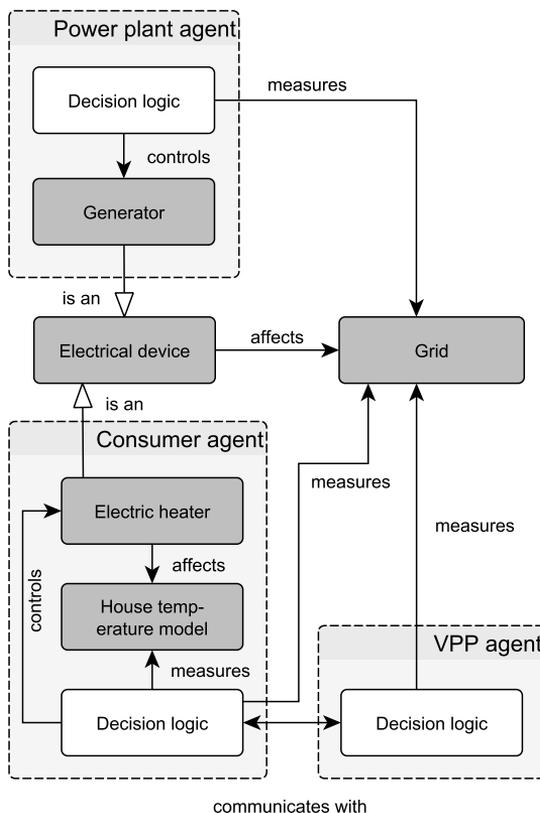
Figure 3.7. Class diagram of the proposed agent-based model. (PIII)

The communication channels were equipped with models for varying latencies and packet drop probabilities. Figure 3.8 shows the resulting step response result with the large sudden production outage, with drastically varying communication latencies. The size of the plant under consideration was the largest single production facility in Finland (Olkiluoto nuclear plant) providing 880 MW. The 1000 consumers that were simulated were scaled to be able to provide similar power in order to test grid-scale responses. The simulations are displayed for the average over 1000 runs as well as the 50th and 95th percentiles, showing the distribution of possible reactions with different realized communication latencies. The decision logic of the aggregator (VPP agent) instructs the consumer agents to defer their consumption relative to the measured frequency. The step response was found to be suitably regular even with the extreme latencies, and the stability of the system was not seen to be under threat. In addition, the advantages of decentralized frequency control (Fig. 2.2) with local frequency measurements and personalized frequency thresh-

olds were highlighted (see PIII). The decentralized approach was able to near-instantaneously provide similar responses.
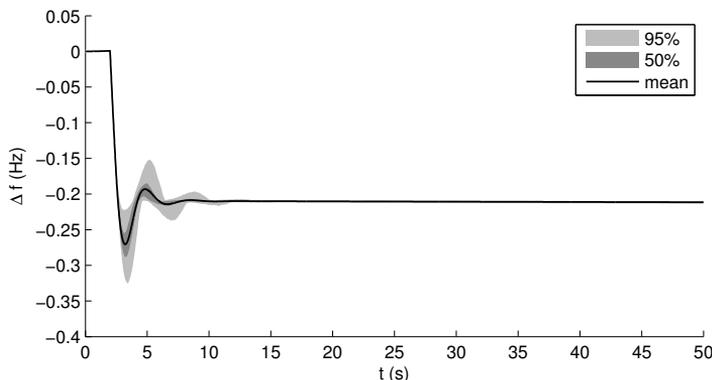
Figure 3.8. The behaviour of the grid frequency with varying latencies, where the shaded areas denote the percentiles (50th and 95th) within which the different runs fall under. (PIII)

Virtual power plant coordination

A similarly structured agent-based model was also utilized in the studied case, where the aggregator and consumers attempt to act on three different states of operation (Publication IV). A model was proposed for maintaining the production–consumption balance in *normal*, *emergency* (FCR-D) and *restoration* states. The emergency state is again invoked with a large imbalance resulting from a power plant outage. Before the outage during the *normal* operation, the consumers minimize their costs relative to the day-ahead market price. In addition, a demand bidding algorithm is proposed to act on the balancing market (precursor to the one presented in (3.19)–(3.20)). In case there is a disturbance event in the grid, the *emergency* state is activated and the thermostat set-points of the direct electric heating loads of the consumers are controlled to provide the disturbance reserve. Then, during the *restoration* state, the bidding is again utilized to remove the imbalance. Additionally, the direct electric heating loads are randomized to minimize the severity of the payback effect resulting from shifting their consumption (see PIV). The proposed forced switching algorithm reduces the effect of synchronization of the thermostats when the emergency state has been activated.

3.3.2 Optimizing flexibility for frequency markets

In this section the intra-day flexibility and frequency control methods from the previous results are used to build a new model that is used to simulate the optimization of frequency market participation (FCR-N) for a group of residential consumers. The aim was to investigate methods for optimizing flexibility and analyze the results.

Proposed model

The considered system was again composed of consumers with generic energy storages and energy demand profiles. The optimization is composed of two objectives consisting of the aim of minimizing day-ahead acquisition costs and the target of maximizing available flexibility. These two competitive objectives in this heuristic optimization were combined by a weighting factor that is chosen by the aggregator. In addition, target profiles ($T_{\uparrow,t}$ (kW) for increase and $T_{\downarrow,t}$ (kW) for decrease) for the flexibility were formed from the expected demand for frequency reserves, estimated from historical data. The optimization problem is then formulated as

$$\min \sum_{t=1}^{H} \left(K_{s,t} P_t + \frac{w^2}{\left(\sum_{t=1}^{H} T_t^2\right)} \left((T_{\uparrow,t} - \delta P_{\uparrow,t})^2 + (T_{\downarrow,t} - \delta P_{\downarrow,t})^2 \right) \right) \qquad (3.32)$$

s.t. $(3.3) - (3.5) \quad \forall P_{n,t} \quad \forall n \in \{1, \ldots, N\}, \ t \in \{1, \ldots, H\}$ \hfill (3.33)

$$P_t = \sum_{n=1}^{N} P_{n,t} \qquad (3.34)$$

$$\delta P_{\uparrow,t} = \sum_{n=1}^{N} \delta P_{\uparrow,t,n} \qquad (3.35)$$

$$\delta P_{\downarrow,t} = \sum_{n=1}^{N} \delta P_{\downarrow,t,n} \qquad (3.36)$$

$(3.3) - (3.5) \quad \forall P_{n,t} + \delta p_{\uparrow,n,t}^{k} \quad \forall n \in \{1, \ldots, N\} \ t, k \in \{1, \ldots, H\}$ \hfill (3.37)

$$\delta p_{\uparrow,n,t}^{k} \begin{cases} = 0 & \text{if } t < k \\ = \delta P_{\uparrow,n,t} & \text{if } t = k \\ \leq 0 & \text{if } t > k \end{cases} \qquad (3.38)$$

$$\delta p_{\downarrow,n,t}^{k} \begin{cases} = 0 & \text{if } t < k \\ = \delta P_{\downarrow,n,t} & \text{if } t = k \\ \geq 0 & \text{if } t > k \end{cases} \qquad (3.39)$$

$$\delta P_{\uparrow,n,t}, \ -\delta P_{\downarrow,n,t} \geq 0 \qquad (3.40)$$

$$\delta P_{\uparrow,n,t} = - \sum_{k=t+1}^{H} \delta p_{\uparrow,n,k}^{t} \qquad (3.41)$$

$$\delta P_{\downarrow,n,t} = - \sum_{k=t+1}^{H} \delta p_{\downarrow,n,k}^{t} \qquad (3.42)$$

where the cost function (3.31) consists of the acquisition costs relative to the expected day-ahead price $K_{s,t}$ and a weighted cost that considers the amount of reserve commitment. The charging schedules have to again obey the storage limits before (eq. (3.32)) and after (eq. (3.36)) the potential demand response. The amount of committed reserves ($\delta P_{\uparrow,t,n}$ and $\delta P_{\downarrow,t,n}$ (kW)) have to be then able to be rescheduled as $\delta p_{\uparrow,n,k}^{t}$ (kW) and $\delta p_{\downarrow,n,k}^{t}$ (kW). The rescheduling consists of the potential hourly DR ($\delta P_{\uparrow,n,t}$ and $\delta P_{\downarrow,n,t}$ (kW)) and the following hours where the charging is rescheduled to (eq. (3.38)–(3.39)). The rescheduled charging is then also constrained by the energy storage and demand (eq. (3.37)). The optimization was solved using a quadratic programming solver, by decomposing the problem w.r.t. single consumer problems. An iterative approach was utilized where the optimization is iteratively solved such that only a single

consumer's optimization variables are optimized, while all the previously optimized values of other consumers are kept constant. The constraints are also utilized for a single consumer at a time. The optimization is then iterated until it converges sufficiently.

Results

Figure 3.9 displays the resulting aggregate day-ahead consumption plans, when the weight is varied from 0.001 to 150. The weight represents the balance between valuing reducing costs of electricity acquisition and risks of reserve participation. 50 consumers scaled to 5000 households were utilized with prices obtained from the year 2013. Both of the optimized plans avoid consumption during the higher price periods denoted by the dashed line. However, when a higher weight is placed on the flexibility, the consumption profile is flatter, affording more flexibility in the consumption.
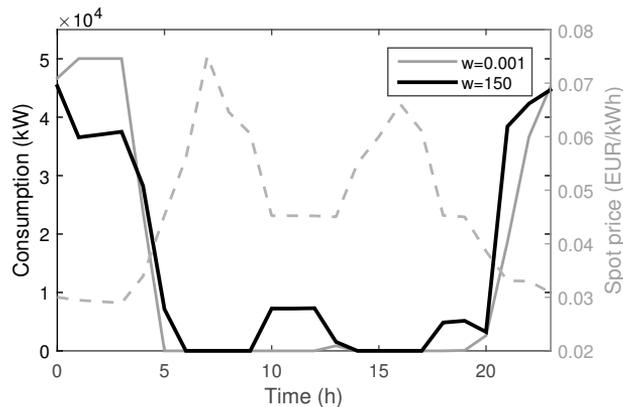
Figure 3.9. The optimized consumption plans with different amounts of flexibility on a particular day. In addition, the spot price for the day is illustrated with the dashed line. (PV)

Figure 3.10 displays the profit of the aggregator after acquisition costs, received reserve compensation and compensation given to the consumers for their participation. The profits can be seen to increase with the increase in the flexibility weight, until they start to dip off, due to the increase in the acquisition costs and the given consumer compensation. In addition, the variance of the profit increases due to the uncertainty in the received profit from the reserves. The results indicate that participation in the frequency reserve market could be profitable. However, the uncertainties in the prices should perhaps be accounted for.
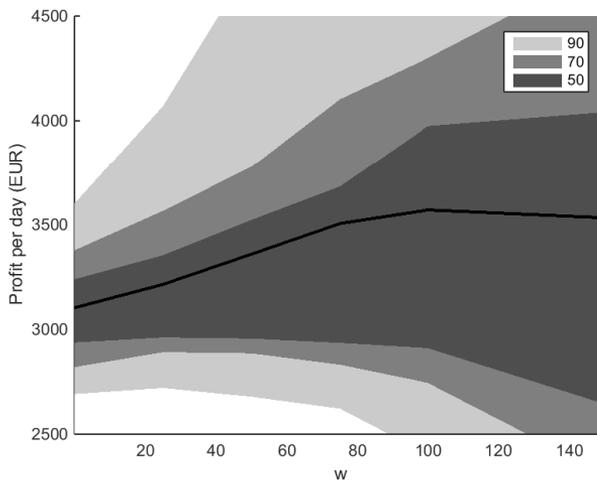
Figure 3.10. The resulting mean daily profit with varying flexibility weights w, including the 50th, 70th and 90th percentiles. (PV)

3.3.3 Including uncertainties in the day-ahead planning

Similarly to the previous publication (Publication V), the problem of optimizing day-ahead plans of residential consumers was again considered for participation in frequency reserves (FCR-N). However, the optimization was now implemented with more detailed consideration for the related uncertainties and coordinating the consumer schedules with respect to the the aggregate plans (Publication VI).

Proposed model

In the proposed model, the consumers were again modelled as residential detached houses with heating demand and energy storages. The heating demand profiles for the consumers were generated from a thermal model of a house [183] and temperature profiles from the Helsinki region. The uncertainty in the amount of demand due to changes in the external temperature and the resulting total reserve activation were accounted for with constraints limiting the expected state-of-charge of the storages within desired limits. The problem is formulated as a stochastic program to take into account the uncertainties in the day-ahead acquisition and reserve prices. The optimization was again decomposed so that the solution could be obtained in a distributed fashion, while partly preserving the privacy of the individual consumers. In addition, while the availability of a

prediction model with a certain accuracy is assumed for the acquisition market prices, a model is devised and its parameters estimated for the frequency reserves. Reserve activation that happens during the hour is assumed to be implemented with some previously discussed method [30, 32, 81, 82, 84–89], which can coordinate the individual charging rates in order to provide the required changes to the aggregate load. Only the resulting hourly deviations are then considered.

In the proposed optimization formulation, the aggregate reserves had to be known before the prices are revealed and thus had to be coordinated to be equal over the scenarios of the stochastic program. In addition, a price-based method is utilized for coordinating the aggregate increase and decrease capacities to be equal in size. In practice, a Jacobi-Proximal variation [160] of the alternating direction method of multipliers (ADMM) is utilized in iterating the coordinating prices. The optimization is performed in two stages, where at first the consumption plans are solved when the reserve and electricity prices are not known, and then in the second stage the actual consumption schedules are calculated with regards to the realized prices. The model is defined as

$$\min g_n(\boldsymbol{x}_n) = \frac{1}{\Omega} \sum_{\omega_1=1}^{\Omega} \Big(\sum_{t=1}^{H} \big(K_{s,t}^{\omega_1} P_{n,t}^{\omega_1} - K_{r,t}^{\omega_1} \delta P_{n,t}^{\omega_1} \big) \Big) \Delta t \qquad (3.43)$$

$$\textbf{s.t.} \quad 0 \le P_{n,t}^{\omega_1} \le P_{max,n} \qquad (3.44)$$

$$0 \le \delta P_{\uparrow,n,t}^{\omega_1} \le P_{max,n} - P_{n,t}^{\omega_1} \qquad (3.45)$$

$$0 \le \delta P_{\downarrow,n,t}^{\omega_1} \le P_{n,t}^{\omega_1} \qquad (3.46)$$

$$0 \le \overline{C}_{n,t}^{\omega_1,\omega_2} \le C_{max,n} \qquad (3.47)$$

$$\overline{C}_{n,t}^{\omega_1,\omega_2} = C_{n,0} + \sum_{k=1}^{t} \big(P_{n,k}^{\omega_1} + \overline{\delta P}_{n,k}^{\omega_1,\omega_2} - Q_{n,k}^{\omega_1}/\eta_n \big) \Delta t \qquad (3.48)$$

$$\forall \omega_1 \in \{1,\ldots,\Omega\}, \, t \in \{1,\ldots,H\}$$

where the shorthand

$$\delta P_{n,t}^{\omega_1} = \frac{1}{2}(\delta P_{\uparrow,n,t}^{\omega_1} + \delta P_{\downarrow,n,t}^{\omega_1})$$

is used to the the amount of reserves that are committed to by the consumer. The amount of activated reserves is relative to the average of the cumulative realized grid frequency deviation over the operating hour, which is assumed to be normally distributed. The average realized activation $\overline{\delta P}_{n,t}^{\omega_1,\omega_2}$ (kW) of the reserves for a particular hour t during the operating day can then be calculated with

$$\overline{\delta P}_{n,t}^{\omega_1,\omega_2} = \mathbf{1}_{\omega_1,t} \frac{\sigma_f}{\sqrt{2\pi}} (\delta P_{\uparrow,n,k}^{\omega_1} - \delta P_{\downarrow,n,k}^{\omega_1})$$

where σ_f^2 denotes the variance of the aggregate hourly reserve activation. The indicator function

$$\mathbf{1}_{\omega_1,t} = \begin{cases} 1 & \text{if } K_{r,t}^{\omega_1} \neq 0, \\ 0 & \text{if } K_{r,t}^{\omega_1} = 0. \end{cases} \tag{3.49}$$

limits the reserve operation to hours where any reserves have actually needed in the market (i.e. hours where the reserves are priced at zero).

The reserve participation consists of the up ($\delta P_{\uparrow,n,t}^{\omega_1}$ (kW)) and down ($\delta P_{\downarrow,n,t}^{\omega_1}$ (kW)) capacity that the consumers commits to providing at time t. The expected storage level $\overline{C}_{n,t}^{\omega_1,\omega_2}$ (kWh) can be calculated from the forecasted hourly heating demand $Q_{n,k}^{\omega_1}$ (kW), the initial state of charge of the storage $C_{n,0}$ (kWh), and the coefficient of performance of the heating device in question η_n. More specifically, constraint (3.43) limits the charging rate to a maximum value. The reserves are provided by changing the storage charging rate, which can only increase the charging to its maximum rate (constraint (3.44)) and decrease to zero (constraint (3.45)) In addition, the energy storage state of charge should be on average able to provide adequate power to satisfy the heating demand (constraint (3.46)) and the expected energy storage charge is defined in eq. (3.47).

The aforementioned consumer cost can also be presented in a more concise fashion augmented with the constraints as

$$G_n(\boldsymbol{x_n}) = \begin{cases} g_n(\boldsymbol{x_n}) & \text{if } \boldsymbol{x_n} \in \mathbb{X}_n \\ \infty & \text{else} \end{cases} \tag{3.50}$$

where $\mathbb{X}_n$ is a set defined by the constraints (3.44)–(3.48). The aggregate problem can then be formulated as

$$\min \sum_{n=1}^{N} G_n(\boldsymbol{x_n}) \qquad \text{s.t.} \sum_{n=1}^{N} A\boldsymbol{x_n} = \boldsymbol{c} \tag{3.51}$$

where the matrix A and vector $\boldsymbol{b}$ are chosen such that aggregate consumption and reserve commitment are equal between the considered scenarios. The aggregate problem can then be solved by iterating over Algorithm 1, where the consumers solve in parallel the Jacobi-Proximal ADMM -augmented problem after which the prices $\boldsymbol{\lambda}$ (€/kWh) are updated.

Algorithm 1: Solving day-ahead optimization using Jacobi-Proximal ADMM

$\boldsymbol{\lambda}^0, \boldsymbol{x}_n^0, \leftarrow 0$

for $k = 0, 1, \ldots$ **do**

$\quad \boldsymbol{x}_n^{k+1} = \arg \min G_n(\boldsymbol{x}_n)$

$\qquad\qquad + \frac{\rho}{2} \left\| A\boldsymbol{x}_n + \sum_{i \neq n} A\boldsymbol{x}_i^k - c + \frac{\boldsymbol{\lambda}^k}{\rho} \right\|_2^2$

$\qquad\qquad + \frac{1}{2} \left\| \boldsymbol{x}_n - \boldsymbol{x}_n^k \right\|_S^2 \qquad\qquad\qquad \forall n$

$\quad \boldsymbol{\lambda}^{k+1} = \boldsymbol{\lambda}^k - \gamma\rho \sum_{n=1}^N A_n \boldsymbol{x}_n^{k+1}$

end

Results

1000 consumers were simulated for 100 days by at first optimizing the aggregate bids to the day-ahead markets and then optimizing the actual schedules w.r.t. the realized prices. The different cases that were compared in the simulations consisted of

- *JP-ADMM*, where the proposed optimization is run in its entirety

- *EVP*, where the expected value problem is solved without considering the uncertainties

- *w/o reserves*, where the reserves were not included

- *w/o optim.*, where the consumers do not optimize their consumption plans at all

The main simulations (*JP-ADMM*) were compared to cases where the expected value problem (*EVP*) was solved without consideration for the uncertainties, as well as the case *w/o reserves* where the reserves are not included in the optimization. The resulting schedules for aggregate charging and reserves participation are presented in Fig. 3.11 for a particular day. There are slight differences between the planned schedules of the different cases, which then result in different costs after the prices in the markets are revealed.
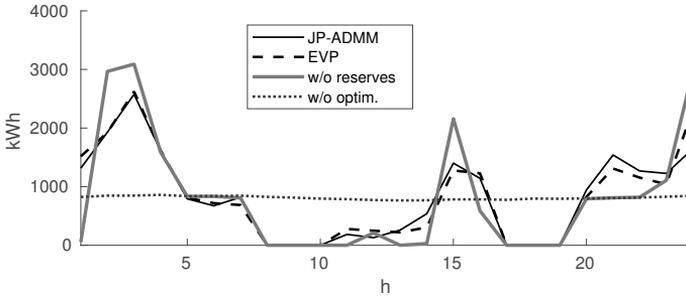
(a) Aggregate consumption schedules optimized with JP-ADMM, EVP, without reserves participation and without optimization.
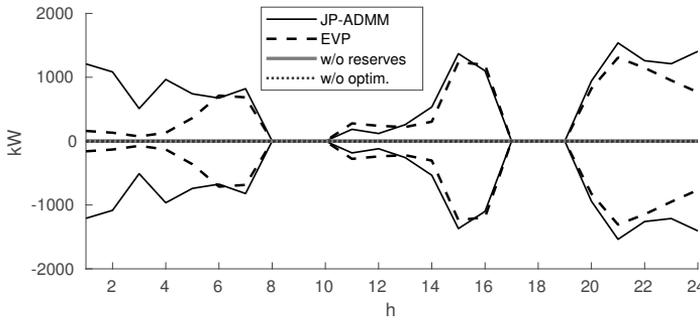
(b) Reserves participation of the different optimization approaches.

Figure 3.11. Resulting consumption and reserves participation schedules on the first day of the simulations. (PVI)

The resulting costs vary between the examined days due to the different consumption and price levels, so the different optimization cases are all compared to the *EVP* solution. Figure 3.12 shows a box plot of the compared daily per consumer costs, where the costs can be seen to increase as the complexity of the optimization is decreased. According to the simulations, the costs can be significantly reduced by optimizing w.r.t. the electricity price and consistently further reduced by including participation in the frequency reserves. The savings could amount to 22.5% when compared to *w/o optim.* In order to further improve the performance, more heterogeneous consumers and appliances could be included in the formulation.
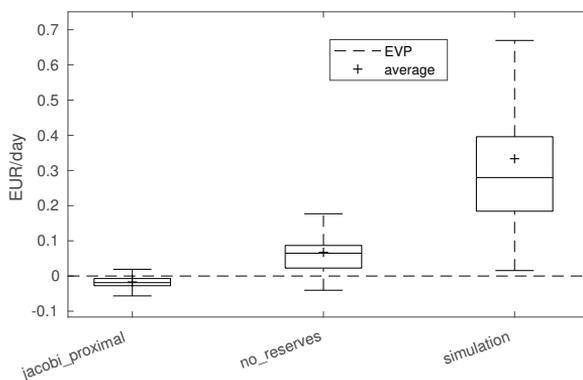
Figure 3.12. Box plots of per consumer per day cost changes when compared to the EVP solution (with 25th and 75th percentiles), as well as mean values ('+'); lower is better. (PVI)

3.4 Summary of results

The DR approaches proposed in this thesis provided several methods for the planning of aggregate residential consumption schedules under various uncertainties. Several novel optimization methods were proposed and the simulations indicated their financial viability. In addition, the amount and appropriate timing of flexibility in the consumption plans was chosen as a concern. This flexibility was then utilized in multiple simulations for various hourly demand response purposes and finally frequency control.

An optimization formulation was developed for deciding the prices that an aggregator charges from its independently acting customers (PI). In addition, a method was also introduced for determining appropriate discounts to these day-ahead prices, in order to alter the consumption plans. The simulated results suggest that an aggregator could choose dynamic electricity prices that would defer the consumption of independent residential customers to desired hours. The optimized dynamic prices could offer slightly smaller and less varying costs than static TOU prices for the aggregator.

In addition, various DR approaches were formulated and compared for their achievable intra-day flexibility. The simulations indicated that different contracts limiting the direct extent of aggregator control on the consumption could have significant effects on the level of DR that could

be reached. With chosen assumptions, when the aggregator has more direct control over the aggregate consumption profile it could change the consumption profile significantly more than in the case where the consumers directly control their own costs. Furthermore, the results indicated that effective utilization of hourly DR could be achieved within the current market conditions, and could be further improved if considered in the day-ahead planning phase (PII).

An agent-based model was devised in Publication III in order to simulate the application of distributed demand response in frequency control. Especially the effects of communication latencies on emergency reserve activation were examined. It was found that centralized control even with highly varying latencies was found feasible in the case of a single large production outage, albeit with slight delays and variance in its operation.

Furthermore, distributed optimization methods for constructing day-ahead plans for frequency reserve participation were developed in publications PV and PVI, and the potential for monetary gains was verified based on extensive simulations. The proposed models consisted at first of a heuristic optimization for investigating the trade-off between the amount of reserve commitment, and potential benefits and their variance (PV). Then in the second model, the uncertainties in day-ahead prices and consumption were taken into account (PVI).

4. Discussion and future work

The presented control approaches and optimizations could only be achieved after considerable investment in appropriate computational and communication infrastructure. The required appliances as well as their installation and maintenance could outweigh the current benefits. However, other uses for the infrastructure could be envisioned as well. The optimizations that were performed would have to be also performed in a timely manner in order to perform the required market actions. For the day-ahead case the optimizations are not as time-sensitive and the planning for day-ahead markets could In general, the presented optimizations were completed at most in the order of seconds per consumer. The distributed nature of the majority of the optimizations For the intra-day optimizations, further time sensitivity has to be considered depending on the application. Interoperability between the participating appliances over heterogeneous communication networks and applications will still require extensive research [184]. In addition, continued measurements are needed from the controlled temperatures, consumer satisfaction as well as the condition of the grid. However, varying levels of optimization for the markets could be achieved with more limited implementations. For example, only the day-ahead market could be considered and price elasticity or direct control utilized to optimize acquisition costs, in contrast to constructing complicated bidding structures for intra-day or participation in reserves. Increased electricity prices and larger variation in the prices (esp. reserves) are possible with the increase in intermittent renewable generation, and would make the proposed demand response methods more lucrative. However, the implementation and operating costs would have to be studied further in order to evaluate the financial viability of the methods. The grid tariffs and taxes are also a major portion of the total electricity costs of the consumers. There are various approaches to grid

tariffs such as time of use rates or power-based tariffs that could affect the distribution of the costs as well as the resulting optimization algorithms. Changes in energy markets in general could offer better opportunities (via e.g. power-based tariffs) for responsive demand to be included in the operation of the markets and enhance the viability of distributed optimization methods such as the ones presented in this thesis.

Home energy management systems could however provide benefits beyond the proposed dynamic demand response programs, thus easing their market penetration. For example, improvements on the level of comfort of the consumers and general energy efficiency could be envisioned without elaborate market participation. Nevertheless, adequate models of house heating dynamics and other consumption patterns would be nearly essential, either on the aggregate or consumer level. The parameters of the dynamics could then be continuously estimated from measurements of the realized temperatures and heating [185–187]. The accuracy of the required models and involved data is a topic that requires still further research before the proposed methods could be implemented on a larger level.

Actually controlling the energy consuming devices requires suitable development and deployment of connections in the houses and their energy management systems, as well as careful considerations for the level of comfort that the different devices have to provide. In order to further ensure that comfort is not endangered, robust optimization approaches could be utilized, or alternatively chance constraints. The residential houses that were considered acted only as electricity consumers, while in case they were to include local production or even just energy storages [188], they could act as *prosumers* by feeding electricity also back into the grid [189, 190]. Additional control and contract considerations would however have to be made with regards to compensations and ensuring the balance of the grid. Furthermore, diverse contracts will most likely be essential for maximizing consumer participation [71]. In general, involving DR into the relevant markets has some limitations, regarding e.g. regulation and bid sizes [191], that have to be considered. However, large consumption can already operate in multiple markets [178], and smaller consumers can purchase electricity relative to the spot price and thus participate in demand-side management while reducing their own costs.

Future research could also expand upon the presented work by including more detailed bidding into the optimization algorithms of the aggre-

gator, beyond the single price-taking bids considered. Also currently the proposed methods focused on the short-term daily costs, while in practice longer contracts and investment costs should probably be considered as well. The flexibility of the consumers could also be quantified with a more rigorous mathematical model, especially for the aggregate levels, which could help with investigating longer timescales. In addition, the intra-day decisions made regarding market and reserve participation could be further improved for example with the application of linear decision rules [135, 192] in order to account for the potential of independent hourly decisions. As the amount of responsive demand that participates in the relevant markets grows, the prices of those markets could also be affected, and thus considered in the optimizations. Furthermore, the impact of a large amount of responsive demand in the various markets could potentially also result in problems for the grid as a whole, and should be carefully considered [193, 194]. The market structures could also potentially change even more drastically, resulting in different approaches that would have to be developed.

The energy storages that were considered were mostly of a general variety, such as storage space heating or large dedicated batteries. However, different solutions would require then specialized consideration in the cost functions and especially constraints of the consumers. For example, personal electric vehicles could be utilized for similar objectives, however with the restrictions that the storage has to filled before some given time and the storage might not be always available. Nevertheless, a larger and especially more diverse population of storages is increasingly more beneficial for utilizing demand response in multiple different timescales. Furthermore, accounting for other energy sinks could be envisioned both during modelling energy consumption forecasts and especially in formulating the optimization models. The considered heating model could easily be expanded to cover cooling demand as well. In addition, other schedulable appliances such as dishwashers and washing machines could be incorporated into the models, further enhancing the DR potential.

5. Conclusions

Demand response could provide a welcome increase to the amount of control to the consumption–production balance of the electrical grid. However, multiple aspects in integrating residential consumption with maintaining the balance should be taken into account (see e.g. Section 2.1.2). In particular, while the electricity consumption of residential consumers offers a lucrative opportunity for fast responses, their effect has to be coordinated without markedly affecting their comfort, and the changes in consumption have to be compensated to the consumers. In this thesis, the challenge of achieving changes to consumption profiles of independently acting consumers was considered, as well as coordinating the planning and control of demand response, for frequency reserves in particular. The objectives of an aggregating retailer of utilizing the responsive demand for financial gains were especially considered with consumers that are attempting to minimize their own costs. The aggregator was assumed to operate on the day-ahead and intra-day markets for energy and frequency reserves, while the considered consumers consisted of residential houses with energy storages. The research produced approaches for controlling the consumption for the various markets, and the results indicated that the proposed approaches could to some extent increase the income of the aggregator and reduce the costs of the consumers within the current market conditions. Improved performance could be envisioned i.a. with more diverse consumption sources as well as the inclusion of planning for markets with longer timescales.

The main results were outlined in Section 3.4 and were supportive of the main hypotheses laid out in Section 1.2, which stated the possible importance of the difference in control approaches for the available flexibility, and the potential for frequency control. Within the carried out research, several frameworks were proposed for an aggregator for forming day-

ahead consumption plans by shaping consumer electricity prices (PI), as well as by more directly controlling the loads (PII). Firstly, the optimization of consumer prices could enable shaping of the consumption profile, without the uncertainties and possible balancing costs of direct spot market pricing (PI). Some intra-day modification of the day-ahead plans were also found to be possible with a developed discount mechanism. Then, a centralized optimization formulation was devised which included in the day-ahead planning the potential for intra-day DR, which was then found to be an improvement over the alternative case where consumers independently optimize their consumption relative to the spot price and further offered incentives (PII). The results from the proposed approaches suggest that the partly independently acting consumers with automated DR capabilities could be reactive to various incentives for shifting their consumption, while preserving their level of comfort. However, independently optimizing consumers might be difficult to be sufficiently incentivized to shift their consumption during the day if they only consider their direct electricity costs that are relative to the day-ahead market price. With more direct access to the loads when the need for intra-day flexibility is taken into account, the proposed direct load control methods indicated even lower overall costs. Therefore, it was found that for maximizing the performance of DR, the consumers should be included in the optimization of flexibility in day-ahead planning, either through prices or a centralized approach.

Furthermore, the flexibility of the consumption schedules was envisioned to be utilized for participation in frequency reserves. In Publication III and IV, electricity consumption was found to be suitable for frequency control with a centralized controller over various networks (PIII), as well as for normal operation, disturbance reaction and restoration purposes (PIV). Then, two optimization models were proposed for planning day-ahead schedules of energy storage charging for frequency containment reserves (PV & PVI). The proposed models were devised such that they could be solved using distributed iterative methods, whilst protecting some of the privacy of the individual constraints. The optimization and simulation results supported the presumption that frequency control could be a potential application for the flexibility of the consumption. The uncertainties in demand and prices were included to the problem as well, further improving the performance of the proposed method (PVI). The evaluated simulation scenarios also suggested that frequency market participation

could be financially lucrative. However, in order to realize any of the proposed demand response mechanisms, the implementation and operation costs should be carefully considered. In addition, further research could be focused on involvement in markets with longer timescales and more diverse appliances could be integrated into the proposed frameworks.

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Errata

Publication II

The final term in equation (17) should include Δt and thus be written as $-\sigma_{Q,n}\sqrt{H}\Phi_\epsilon\Delta t$.

Publication V

For clarity, in eqs. (9)–(10) and (13)–(14) $p_{\uparrow,n,k}$ and $p_{\downarrow,n,k}$ should be written as $p^t_{\uparrow,n,k}$ and $p^t_{\downarrow,n,k}$, respectively.

Additionally in eqs. (11)–(12) the conditions should be ≥ 0 and ≤ 0.

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