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## Demand side flexibility optimization for bidding and scheduling problems

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Thesis for the degree of Philosophiae Doctor

Halden/Trondheim, March 2017

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# Preface

This thesis is the result of almost six years' work for the degree of Philosophiae Doctor at the Department of Industrial Economics and Technology Management at the Norwegian University of Science and Technology (NTNU). The work started in 2011, funded by The Research Council of Norway and a consortium of industry partners through *Manage Smart in Smart Grids*, an innovation project for the industrial sector (grant number 20744/S60). A key motivation for starting this PhD project was my ambition to contribute to bridging the gap between the industry and academia in the field of electricity markets in general and Smart Grids in particular. My target was to utilize theories and methods from academia and develop competences and tools applicable to solve problems in the industry. Furthermore, since much of the research in this field is either focussing on technical or economic issues, I found that a joint approach is critical in order to solve future challenges.

Combining a PhD project with a job in the industry is a challenging task, especially in a start-up company, and the fulfilment would not have been possible without the support and help in different ways from many people.

First, I want to thank Bernt Bremdal, who was the project manager for *Manage Smart in Smart Grids*, for supporting me when I introduced my candidature to the PhD position. Next, Dieter Hirdes, who was my manager in NCE Smart Energy Markets at that time, for preparing an arrangement that made it possible to combine the PhD project with an ordinary job.

The next step was to find an institution and a professor with the right competence and approach to support the project. I was lucky to find Professor Asgeir Tomasgard and the network around him. Asgeir immediately had a very clear vision about how we could run the project, alternative research perspectives we could choose and relevant courses I could take. I want to thank Asgeir for believing in me and for his supervision, in particular when it comes to giving advice about different approaches and perspectives to the problems. Sometimes he let me walk down dead ends, which was frustrating, but proved to be very enlightening.

Further, I have appreciated the cooperation with my co-supervisor, Professor Magnus Korpås. The combination of Asgeir from the department of Industrial Economics and Technology Management and Magnus from the department of Electrical Power Engineering was very useful, since they represent different communities and have contributed from different angles.

I also want to thank Stein-Erik Fleten for the cooperation on the bidding-articles.

During my time as a PhD student I have been the co-supervisor for many master students. This has been very valuable for me, and I want to thank the students Victoria Fearnley Landmark, Victoria Lervik, Christian Svendby, Hege Grønning Vatn, Stine Anette Berntsen, Siri Olimb Myhre and Siri Bruskeland Ager-Hanssen for their contributions. Their ideas and results have been important input to my work. In addition, I had great support in cooperating with the PhD students Pernille Sire Seljom, Karen Byskov Lindberg and Camilla Thorrud Larsen. In particular, they were a great support during the courses and exams.

It was crucial for me that the research should address problems relevant for the industry and that the results should be applicable to the industry's real life problems. My work would not have been possible without fruitful discussions about current and future challenges and the provision of data from Fredrikstad Energi (Vidar Kristoffersen), Statsbygg (Ole Aasen), Norske Skog Saugbrugs (Ander Hedin), Fortum Charge and Drive (Joakim Sveli), Statkraft (Hanne Guri Bøhmer Arnø) and several others.

I also want to thank all my colleagues at NCE Smart Energy Markets and eSmart Systems in Halden, in particular those involved in the *Manage Smart in Smart Grids, ChargeFlex* and *EMPOWER* projects. It has been extremely meaningful to work in such an enthusiastic environment which also appreciates the outcome of my research. Special thanks to Dang Ha The Hien for help when I was stuck with programming problems. A great thank also to Knut H. H. Johansen and Knut Eirik Gustavsen for the cooperation in different companies and projects through the last 25 years and for constantly supporting and believing in me.

Finally, I want to thank my wife through many years, Tove, for standing by my side also during this challenging project, despite my frustrations, sleepless nights and distant periods (physically and mentally).

Halden/Trondheim March 2017

Abstract

Due to technology developments and policy measures to combat climate change, electricity systems and markets all over the world are undergoing significant changes. One driver behind these changes is the integration of distributed generation from renewable sources like sun and wind, characterized by intermittency, uncontrollability and difficulty in forecasting. Another driver is new types of electric demand for heating, charging of electric vehicles and power-demanding appliances. For the electricity system, these changes mean new challenges due to more power variability, less predictability, reverse power flows, greater variations in voltage levels and higher peak loads. Such changes increase the value of flexibility in the electricity system, both at the wholesale side and in particular at the demand side. At the same time, the system's ability to deliver demand side flexibility is increasing due to the introduction of distributed storage technologies, advanced metering infrastructure and intelligent ICT solutions. This is the core of the Smart Grid concept.

To introduce incentives for participation in demand side flexibility programs, changes are also expected in the economic system, including new contract types based on indirect and direct control and new market clearing mechanisms. Furthermore, incumbent market roles will change and new market roles, like energy service companies and aggregators, will emerge. For the electricity market participants, this means new opportunities to reduce costs or increase profits. To make optimal trading and operational decisions, advanced decision support systems are needed.

In this thesis we use operations research to formulate mathematical models for the bidding and scheduling processes for different types of market participants and in different contexts. Particularly, we focus on how to properly model the interrelation between the contract and market rules on one side, and the underlying physical energy systems and appliances with technical and comfort related constraints on the other. Due to the growing uncertainty of load, generation and market prices, we also focus on uncertainty handling in the decision process.

The thesis includes four papers:

The first paper, *A stochastic model for scheduling energy flexibility in buildings*, covers the decision problem of a Facility Manager or an Energy Service Company for a building that participates at the retail side of the electricity market aiming at minimizing total energy costs.

The second paper, *Prosumer bidding and scheduling in electricity markets*, models the bidding and scheduling problem for a retailer that also manages flexibility at the prosumers' sites aiming at cost minimization. Bidding is done to a spot-market and imbalances are penalized in a balancing market.

Paper three, *Multi market bidding strategies for demand side flexibility aggregators in electricity markets*, covers the problem of an aggregator that maximizes profit by selling flexibility in multiple, sequential markets.

The last paper, *Direct control methods for smart electric vehicle charging at grid constrained charging sites*, proposes two methods for a Charging Service Manager's problem to schedule the charging of electric vehicles in cases where the capacity is limited.

# Acronyms

| | |
|---|---|
| AMI | Advanced Metering Infrastructure |
| CHP | Combined Heat and Power |
| CPP | Critical Peak Pricing |
| CSM | Charging Service Manager |
| DER | Distributed Energy Resource |
| DG | Distributed Generation |
| DR | Demand Response |
| DS | Distributed Storage |
| DSM | Demand Side Management |
| DSO | Distribution System Operator |
| EV | Electric Vehicle |
| ESCO | Energy Service Company |
| G2V | Grid to Vehicle |
| IoT | Internet of Things |
| LP | Linear Programming |
| MILP | Mixed Integer Linear Programming |
| OR | Operations Research |
| OTC | Over The Counter |
| PEV | Plug in Electric Vehicle |
| PHEV | Plug in Hybrid Electric Vehicle |
| PV | Photo Voltaic |
| PX | Power Exchange |
| QP | Quadratic Programming |
| RTP | Real Time Pricing |
| SP | Stochastic Programming |
| ToU | Time of Use |
| TSO | Transmission System Operator |
| V2G | Vehicle to Grid |
| VPP | Virtual Power Plant |

# Content

# Chapter 1. Introduction

This thesis presents techno-economic models in Smart Grids, with focus on optimization models for bidding and scheduling of flexibility at the demand side of the electricity market. The thesis is divided in two main parts.

Part one describes the background, motivation and context for the work and consists of four sections. It starts with a brief overview of the traditional electricity value chain, seen both from a technical and an economic perspective. Section two describes ongoing and expected future changes, first seen from a technology perspective and next how these will influence the economic system. Section three is about decision support models, and starts with a brief introduction to operations research, followed by bidding and scheduling models for electricity markets. Lastly, section four gives a summary of the papers included in this thesis.

Part two consists of four papers:

1. A stochastic model for scheduling energy flexibility in buildings
2. Prosumer bidding and scheduling in electricity markets
3. Multi market bidding strategies for demand side flexibility aggregators in electricity markets
4. Direct control methods for smart electric vehicle charging at grid constrained charging sites.

## 1.1. The traditional electricity value chain

This section gives a brief overview of the electricity value chain, first seen from a technical perspective, secondly from an economic perspective. The Norwegian deregulated regime is used as an example, but the basic principles are valid for many countries. The description is intended for non-expert readers and meant to give an overview of features relevant for this thesis. For more comprehensive descriptions, we refer to textbooks like Wangensteen (2011), Kirschen & Strbac (2004) and Stoft (2002).

Notice that the terms **electricity**, **power** and **electric power** are used interchangeably in the literature. In this thesis we intend to use **electricity** when describing the commodity in general and electric energy in particular (as measured in kWh and MWh), and the term **power** for the rate of energy transfer (as measured in kW and MW).

### The technical system

Electricity is traditionally generated in large, centralized power plants, transported through the transmission grid, further through the distribution grid and finally delivered to loads. This is a uni-directional flow from generators to loads. Figure 1.1 gives a simplified overview of the physical system. The arrows indicate the flow of electricity, also called load flow.

Each power plant consists of one or multiple generators that convert an energy source to electricity. Sources can be renewable, like hydro or wind, they may be fossil, like natural gas, oil or coal, or they may be nuclear, like uranium.

In the nationwide transmission grid, the voltage levels are very high, in Norway normally 300 or 420 kV. High voltage levels are used to minimize the grid losses. In the regional and local distribution grids, the voltage is stepwise reduced to lower levels in transformer stations several times. In the Norwegian system 132, 66, 22 and 11 kV are commonly used. The voltage is finally transformed down to 400 or 230 V in a substation and delivered to the loads. The low voltage levels are used for economic and safety reasons. Industrial loads may also be connected at higher voltage levels.

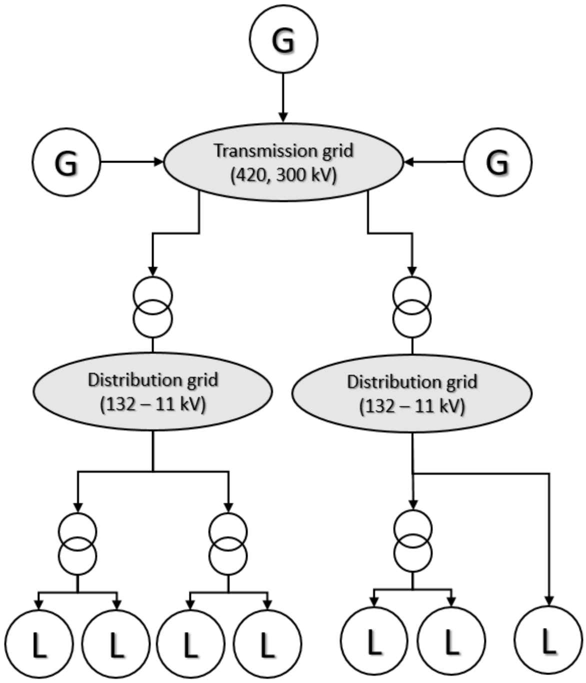


*Figure 1.1. Simplified representation of the physical electric power system*

A load may represent an industrial facility, a commercial building or a residence.

Compared to other commodities and transportation systems, electricity has some special, physical characteristics and features which complicate the design and operation of the total system. In particular, three are relevant for this thesis:

**Overload**. Similar to most other transport systems, the electric grids also have capacity limits. However, since electricity must be consumed instantly when generated, queues can not exist, and the grid must be designed with sufficient capacity to transport the highest amount of load, denoted peak load. Overloading a network component may result in disconnection (by protective devices), unsafe situations (overhead lines sag more than allowed) or reduced lifetime of components. Furthermore, in electricity grids load flow may also be limited due to voltage conditions or redundancy requirements.

**Voltage quality**. The voltage levels must be within specified limits in all parts of the grids. Deviations may lead to malfunction of grid components or appliances inside buildings.

**Frequency**. Electric power must be consumed instantly when generated. In other words, there must be a perfect balance between generation and load at any time. If not, the frequency will deviate from 50 Hz. Large deviations may lead to system instability and black-out situations with large negative consequences for the society.

These features put strong requirements on how the electricity system is designed and operated, and how it is organized.

## The economic system

### The roles and their inter-relations

A number of roles with associated tasks and responsibilities must be in place to ensure that the electricity system is designed and operated cost-efficiently and within safe limits. The Transmission System Operator[1,2] (TSO) is responsible for the development and operation of the transmission grid and for the frequency control. The distribution grids are owned and operated by a number of Distribution System Operators (DSO). In Norway there are currently approximately 125 DSOs, with the main task to deliver electricity to the final consumers. The TSO and DSOs are responsible for the transportation part of the electricity system including overload control, also called congestion management, and voltage control in the respective grids. It is mandatory for each consumer to enter a grid contract with the DSO to which he or she is physically connected. According to the deregulation processes in the early 90s, the TSO and DSOs are monopoly regulated. On the other side, the sales and purchase of electricity are handled in a competitive market. A consumer can freely choose a retailer from which he or she wants to buy the electricity. The retailer buys the needed volumes of electricity at market places organized by the Power Exchange (PX) or directly from a producer through a bilateral contract. The latter is also called over-the-counter (OTC) or off-exchange trading.

Figure 1.2 shows a simplified illustration of the different roles and their relationships, where the monopoly roles are presented to the left and the competitive to the right. The arrows indicate the economic flows between the roles. The producers and the DSOs pay the TSO for

[1] http://statnett.no/

[2] https://www.entsoe.eu/

transmission grid usage, while the consumers pay the DSO for distribution grid usage. The economic conditions are regulated through grid contracts, often denoted grid tariffs.

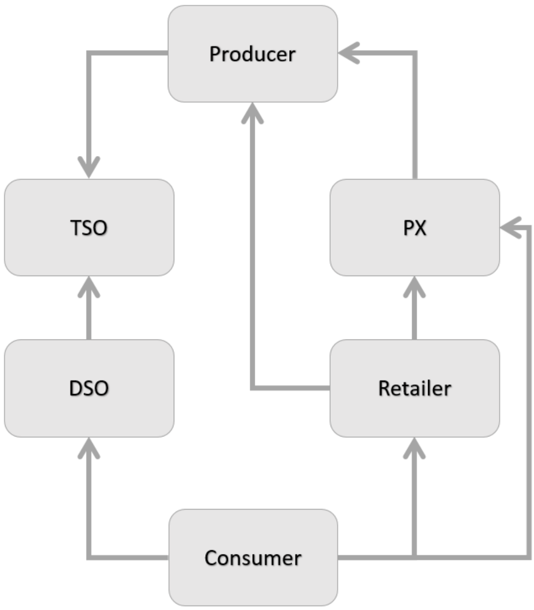


*Figure 1.2. The different roles in the electricity market and their economic relationships*

Each consumer buys electricity from a retailer which can trade either at the PX or directly from a producer. Finally, the producers receive revenue from selling to the PX and retailers.

The economic flows are regulated through different contract arrangements, which can be divided into two different levels: The wholesale market and the demand-side market.

## Wholesale market

Figure 1.3 shows a general and simplified overview of the organized wholesale market places in the current market regime. The figure indicates that trading is done in a partly sequential manner – the further to the right, the closer to real-time operation. The main market is the Day-ahead market, operated by Nord Pool[3]. Here, buyers and sellers submit their bid curves for each hour of the following day. Around noon, the market is cleared, i.e. the PX finds the price that

[3] http://www.nordpoolspot.com/

matches supply (sales) and demand (purchase) hour by hour. Prices and market commitments are then published. Since all market participants bid the volumes they expect to produce or consume, the market is now in balance hour by hour. However, parts of the production and consumption are uncertain since they depend on external factors such as weather conditions. Furthermore, unplanned outages may occur both at the production side, the consumption side or in the grid. Due to these changed conditions, it may be impossible to produce or consume the volumes committed in the Day-ahead market.

To adjust the balance after the Day-ahead market is cleared, the Intraday market can be used. Here, market participants can buy or sell additional volumes to retain balance. While the Day-ahead market is cleared simultaneously for all hours for a day, the Intraday market is cleared continuously, similar to stock exchange trading. Gate closure is one hour before each operational hour. Bids and corresponding commitments in the Day-ahead and Intraday markets are at aggregated, zonal levels.

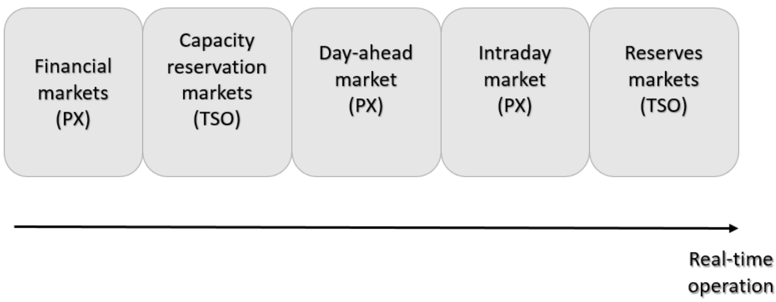


*Figure 1.3. The electricity market structure*

Both the Day-ahead and Intraday markets have the time resolution of one hour and therefore ensure market balance at an hourly level in the planning phase. However, since supply and demand must balance in real time, the TSO organizes a set of reserves markets with different time horizons. The reserves are purchased by contracts or market clearing mechanisms. Primary reserves are generation or load resources that are automatically adjusted in response to frequency deviations in real time. Large, dispatchable generators are typical contributors. If the frequency drops below 50 Hz, the generation is instantly increased and vice versa. In situations where the imbalances last for several minutes, the Secondary reserves will be activated. In order to be qualified to participate in Secondary reserves, a resource must be able to activate within two minutes. Primary reserves will then be released to meet new imbalances.

Similar to Primary reserves, the Secondary reserves are also activated automatically. If the imbalances continue, the Tertiary reserves will be activated to release Secondary reserves. This is a manual process where the TSO contacts the market participant and asks for activation of a resource according to a bid. Such reserves must be activated within 15 minutes. Tertiary reserves are called upon according to a merit order list, where the participants bid their possibility to adjust generation or consumption in terms of pairs of volume and a price. When increased production or reduced load is needed (defined as up-regulation), the TSO activates the cheapest bid first, then the second cheapest and so on. For down-regulation the opposite yields. The Tertiary reserves market is also denoted Regulation power market. While the Day-ahead and Intraday markets are at aggregated, zonal levels, the Reserves markets are at the individual level, i.e. per power plant or industrial facility.

The main objective of the Day-ahead, Intraday and Reserves markets is to ensure balance between generation and load.

After each hour all market participants calculate and report deviations between committed (planned) and real (metered) sale and purchase. Such imbalances are economically settled by the TSO according to imbalance prices, which are calculated based on activations in the Tertiary reserves market. In this way, the market participants are penalized for their imbalances.

For the TSO to ensure that sufficient volumes of reserves are available during the operation, different Capacity reservation markets are organized. Here, capacity is allocated for later use in the reserves markets.

Finally, the PX also organizes trading in financial contracts, where instruments like futures, forwards, options and contracts for difference (CfD) are traded. In Norway, such markets are operated by Nasdaq[4]. Financial contracts are used by the market participants for price hedging and risk management purposes. The contracts have time horizons up to several years, covering daily, monthly, quarterly and annual contracts. Financial markets are outside the scope for this thesis.

[4] http://www.nasdaqomx.com/commodities

## Demand-side market

The previous section described the wholesale market, where producers, retailers and large consumers trade and take responsibility for their own balances. Most of the consumers do not participate in the wholesale market, but buy the electricity they need from a retailer, that acts as the balance responsible party on behalf of a group of consumers. We denote this demand-side or end-user side of the market, which refer to the lower part of Figure 1.2. Each consumer needs to have a grid contract with the local DSO and a supply contract with a freely chosen retailer.

The main purpose of the grid contracts is to cover the DSO's expenses in operating, maintaining and reinforcing the distribution grid. Furthermore, the grid contracts aim at distributing the expenses between the grid users in a fair manner. In the Norwegian regime, the grid contracts are normally based on a two- or three-part tariff, dependent on how the consumer is metered. For periodically metered consumers the payment consists of two components: A fixed fee, which might be based on main fuse size, and an energy fee, which normally is based on metered electricity consumption paid according to a fixed price per kWh. For larger consumers with hourly metering, a third part may exist, based on one or a limited number of the highest metered hourly consumptions within a month. This element is paid according to a fixed price per kWh/h per month and is often denoted power charge.

For retail contracts the variation is larger. In addition to free choice of retailer, the consumer can also select the contract type according to preferences. For consumers with periodically metered consumption, the most common are fixed or variable prices. The latter may be one specified price for a period, for instance a month, or it may follow the Day-ahead market prices. However, although the price varies from hour to hour, the consumption is only metered as an accumulated consumption for a long period, and is distributed according to a pre-defined profile to be able to settle hourly prices. For larger consumers with hourly metered values, the real consumption can be settled according to the market prices, hour by hour.

## 1.2. Changes in the electricity value chain

### Drivers

Today's energy systems are facing radical changes. This is in particular valid for the electricity value chain. Different factors drive this development. On one side, there are climate and energy policies aiming at abating climate changes. The EU 202020-target (ETP SmartGrids, 2007) illustrates what this is about: Greenhouse gas emissions must be reduced, the shares of renewable energy generation must be increased and the energy must be used more efficiently. To reach these goals, authorities in different countries have introduced a wide spectre of incentive regimes and regulations. In addition to policies, the technology development itself is a strong driving force. New technologies relevant for the electricity systems are continuously being developed and improved, which lead to new or more cost-efficient appliances and innovative services.

### Technical implications

To reduce the greenhouse gas emissions from power generation and to increase the shares of renewable generation, more power plants based on renewable sources must be built. One option to reach this goal is to introduce **Distributed Generation** (DG), defined as *electric power generation units connected directly to the distribution network or connected to the network on the customer site of the meter* (Ackermann, Andersson, & Söder, 2001). Several other terms are used, like local generation, decentralized generation, on-site generation and dispersed generation. Typically, DG technologies are small-scale generators in the range from 3 kW to 10 MW (Viral & Khatod, 2012) that produces electricity from renewable sources like wind (wind turbines) or sun (solar photo voltaic (PV) panels)). Compared to traditional, centralized generators (like hydro or thermal power stations), these are characterized by intermittency, uncontrollability and difficulty in forecasting (Kondziella & Bruckner, 2016).

Due to the fossil fuelled combustion engines in cars and trucks, the road transport sector currently accounts for about 23 % of total global energy-related greenhouse gas emissions (International Energy Agency, 2008). To decarbonize this sector, electrification in one possible and promising approach. Rechargeable electric vehicles, also denoted **Plug-in Electric Vehicles** (PEV) is one promising way to reach this goal. Improved battery technologies, new car types and incentive schemes have led to large scale deployment in different parts of the world. Norway has in particular had strong incentives the last years (Figenbaum, Assum, & Kolbenstvedt, 2015; Haugneland, Bu, & Hauge, 2016), including exemption from import tax and VAT, free toll roads, free parking and access to bus lanes. As a result, more than 20 % of the new cars sold in Norway in 2015 were chargeable.

PEVs may charge at home, at a commercial fast charging station or at a parking lot, for instance outside a workplace. While home-charging currently is done at low power levels (2.3, 3.7 or 7.4 kW), higher levels are available at parking lots and fast charging stations (11, 22, 50 and 120 kW are examples). However, even higher power levels are expected to be standard in the future. It is well known that PEV charging will influence the load pattern both for residents and for the distribution grid (Clement-Nyns, Haesen, & Driesen, 2010; Lopes, Soares, & Almeida, 2011). In particular, the grid may be put at stress when many PEVs need to charge simultaneously. Furthermore, the timing of the charging often coincides with the peak load periods. For instance, charging when coming to work in the morning coincides with the commercial buildings' morning peak. Charging in the afternoon when returning from work coincides with the afternoon peak in residential areas.

Recharging of PEVs is not the only type of new electric loads. Electrification of heating sectors is another (Teng, Aunedi, & Strbac, 2016) involving different heat pump technologies. In addition, new appliances for water heating and cooking based on instant heating and induction are penetrating the market. Such technologies increase energy efficiency, but requires large power levels for short time intervals.

Figure 1.4 illustrates how introduction of technologies described above can impact the load profile for households. The upper left part presents average hourly electricity consumption reported in a Norwegian study (Kipping & Trømborg, 2015), showing a clear profile with a morning and afternoon peak. In the upper right part, we have introduced PEV charging at 3.7 kW, which doubles the afternoon peak. Next, in the lower left part we see a possible generation profile from a solar panel. Notice that maximum generation is in the middle of the day, which does not correspond well to the load profile. Furthermore, due to clouds passing by, the generation instantly drops to lower levels for short time intervals and rapidly returns to high levels. Finally, the right, lower part shows the net profile when including PEV charging, PV generation and power demanding appliances. It is possible to observe that the house is delivering surplus electricity in the middle of the day, that the profile has clear spikes in the morning and afternoon, and finally, that the afternoon consumption is higher for a longer time interval. In total, the house's profile is completely changed.

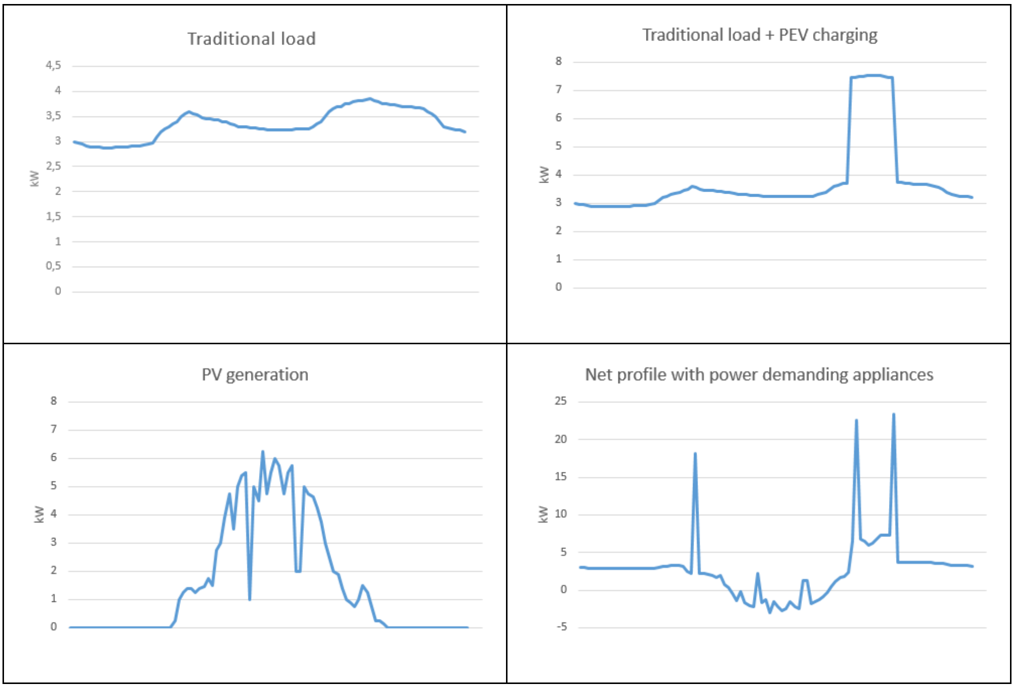


*Figure 1.4. Illustration of load and generation profiles for a household over one day*

This example shows the profile for one single household. When aggregating the curves for all prosumers in a network area or behind a transformer, the spikes will be dampened. Nevertheless, the same trend can be observed here: Increased dynamics, larger peaks and reverse flows. Altogether, such changes may have adverse consequences for the grids, in particular at the lower levels of the distribution grids (Pudjianto et al., 2013), and in particular in parts of the grids where many buildings have the same characteristics and the grid is weak. Therefore, the DSOs' operation of the distribution grids will be challenged in several ways. Eurelectric (2013) states the following issues: unpredictable and bi-directional network flows, greater variations in voltage and different network reactive power characteristics.

These changes increase the need for grid capacity and reserves. The traditional approach to additional needs is to reinforce the grid, i.e. invest in more capacity. However, this is not a straightforward task, since grid reinforcements are very costly, have negative environmental impact and often have long lead times until they are ready for operation. Furthermore, such additional capacity will often have low utilization levels (Teng et al., 2016).

An alternative approach to building more capacity is to utilize flexibility, defined as *the modification of generation injection and/or consumption patterns in reaction to an external price or activation signal in order to provide a service within the electrical system* (Eurelectric, 2014).

Utilization of flexibility in the electricity system is not a new concept. Since supply and demand must match perfectly in order to keep system operation stable and within safe limits, flexibility has been used since the advent of electricity systems. However, this has been done mainly at the centralized level and by flexible generators. The challenges mentioned above mostly emerge at the distribution side of the electricity system, and must be solved there. Hence, the flexibility in central power plants can not be used, and we need to look for flexibility in the distribution grid, which we denote **demand side flexibility**. Eid et al. (2016) characterize demand side flexibility according to five attributes: Its direction (up or down), its electrical composition in power (kW or MW), its temporal characteristics defined by starting time and duration, and its base for location.

An obvious option for demand side flexibility is to change the electricity usage by end-use customers from their normal consumption patterns (Albadi & El-Saadany, 2008), denoted **Demand Response** (DR). Such changes may be done by shifting some loads in time, for instance by charging the PEV during the night, or by curtailing some loads, for instance by disconnecting heat pumps or ventilation fans when direct water heating is ongoing.

Another upcoming option for demand side flexibility is to utilize devices able to store energy at the distribution side of the electricity system. Many different technologies exist, including thermal storages (ice storage, hot or cold water tanks) and electricity storages (batteries) (International Energy Agency, 2014), The latter covers battery banks owned and operated by DSOs or residential systems like Powerwall[5] or sonnenBatterie[6]. Storage systems at the distribution side are also denoted **Distributed Storage** (DS) and may be used to store renewable energy to be used at a later, more beneficial stage (International Energy Agency,

[5] https://www.teslamotors.com/energy

[6] https://www.sonnenbatterie.de/en/start

2014) or to reduce peak loads. Utilizing batteries in electric vehicles for such purposes is also a concept under evaluation, denoted **Vehicle to Grid** (V2G) (Habib, Kamran, & Rashid, 2015).

Developments in the ICT sector also influence the electricity systems at demand side. **Advanced Metering Infrastructure** (AMI), which includes smart meters and a communication infrastructure between the DSO and the consumers, is one important change. Currently, AMI deployment is ongoing in many countries around the world. For example the EU Member States have committed to rolling out close to 200 million smart meters for electricity (Institute for Energy and Transport (IET), 2016). In Norway, all meters will be shifted to smart meters by 2018. In addition to automatic meter reading, and hence increased efficiency in the meter value collection process, AMI gives more detailed information about electricity usage regarding time resolution (down to hourly or 15 minutes' level), possibility to meter several parameters (like reactive power and voltage), two-way communication with the DSO, functionality to disconnect and an open interface for third parties.

Furthermore, automatic building management systems, smart home solutions, apps and smart appliances make it possible to meter, visualize and control the energy consumption, generation and other relevant parameters, down to the device level. This is where the electricity sector meets the **Internet of Things** (IoT), defined as *a global infrastructure for the information society, enabling advanced services by interconnecting (physical and virtual) things based on existing and evolving interoperable information and communication technologies* (International Telecommunication Union, 2012).

By integrating all the technologies described above, we get the **Smart Grid**. Two early and widely accepted definitions are:

- *A Smart Grid uses digital technology to improve reliability, security, and efficiency (both economic and energy) of the electrical system from large generation, through the delivery systems to electricity consumers and a growing number of distributed generation and storage resources* (United States Department of Energy, 2009).
- *A Smart Grid is an electricity network that can intelligently integrate the actions of all users connected to it – generators, consumers, and those that do both – in order to efficiently deliver sustainable, economic and secure electricity supplies* (European Commision, 2006).

The concept of the Smart Grid is illustrated in Figure 1.5, where the blue grid represents both the electrical and information integration of different users. A lot of Smart Grid initiatives are currently ongoing all over the world. An overview of European projects is given in DERlab (2016). The research literature in the field is extensive and growing year by year. Recent reviews and surveys can be found in Esther & Kumar (2016), Haider, See, & Elmenreich (2016), Zehir, Batman, & Bagriyanik (2016)), Hasanpor Divshali & Choi (2016) and several others.

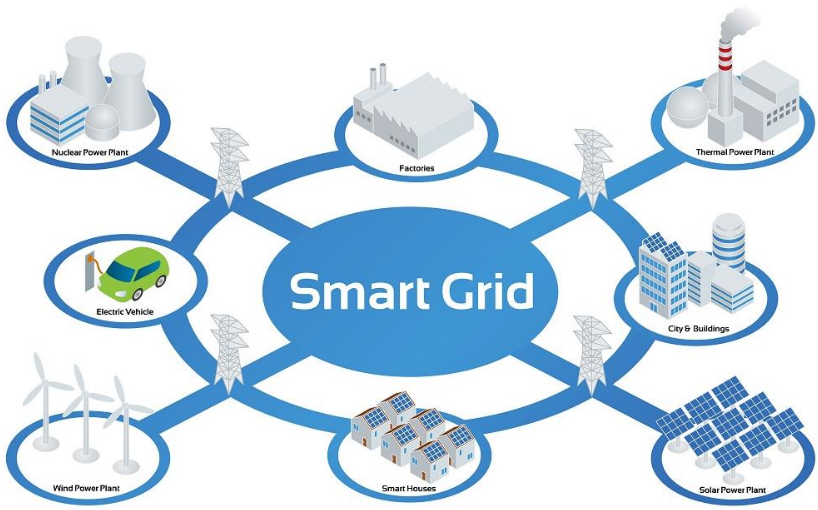


*Figure 1.5. Illustration of the Smart Grid (European technology platform for the electricity networks of the future, 2014)*

As described above, some of the technology changes induce negative consequences for the electricity system. On the other side, some of them can also contribute to increasing the potential for demand side flexibility and hence limit the consequences (O'Connell et al., 2014). This is one of the key objectives with the Smart Grid.

## Economic implications

The previous section described the need for demand side flexibility and how it can be implemented from a technical perspective. Although technically possible, this will not happen without incentives motivating the end-users to participate in flexibility arrangements. Changes are therefore also needed in the economic system, including new contract types and business models, new and changed market roles and new market designs.

One obvious role change is that the consumer turns into a **prosumer**. Grijalva, Costley, & Ainsworth (2011) define prosumer as *an entity that can do at least one of the following: consume, produce, store, or transport electricity*. Since grid companies are responsible for transport, we limit the definition to cover consumption, production and flexibility provision.

## New types of end-user contracts - Indirect control

Electricity prices to consumers have traditionally been flat for longer periods. One reason has been the lack of metering equipment able to meter electricity with sufficient time granularity. Deployment of smart meters opens up for the introduction of different, innovative pricing regimes all the way to the end user. Some of the standard price-based signals and flexible billing methods used are **Time of Use** (ToU), **Critical Peak Pricing** (CPP) and **Real Time Pricing** (RTP) listed in order of increasing complexity and flexibility (Schreiber et al., 2015). ToU rates have fixed prices per different blocks of time in a day. CPP applies extra high rates throughout a pre-specified limited number of hours and can be combined with ToU or flat rates. RTP varies on an hourly basis in accordance with the wholesale market price.

Other price models differentiate between consumption level, denoted progressive power tariffs, like inclining block rates (Mohsenian-Rad & Leon-Garcia, 2010) or subscribed power (Sæle et al., 2015), where the marginal price increases with the quantity consumed. Furthermore, some price models include a peak power fee, sometimes denoted demand charge (Pacific Power, 2015), where the contract contains a fee based on metered maximum hourly or quarterly power out-take over a certain period (The Norwegian Water Resources and Energy Directorate (NVE), 2016).

All these contract types are based on the **indirect control** mechanism (Ygge & Ackermans, 1996), where a central agent (e.g. the DSO) sends a signal (e.g. a price) to its customers, and the customers respond according to their preferences. Indirect control is also called price-based control and decentralized control, since the decision is taken by each end-user.

Advantages with the indirect control mechanism is that it requires little technical infrastructure between the agent and the customer, and that the already existing contractual relation can continue. Hence, the method is relatively easy to implement. On the other side, the prosumers respond also when the electricity system does not need adaptations. Further, this mechanism does not guarantee that the required response is obtained. From the perspective of the prosumer, indirect control may be perceived as a penalty.

Response to the price signals may be done manually or semi-automatically, for instance by using timers. However, we do not believe that the prosumers will be motivated to be very active, observe prices and manually adjust set-points, but that the response will be handled by software or service providers which we call **Energy Service Companies** (ESCOs). Figure 1.6 shows the economic relations between the prosumer and the traditional DSO and retailer, expanded with the ESCO role. The contract with the ESCO will regulate the services and how the cost reductions are shared between the ESCO and the prosumer.

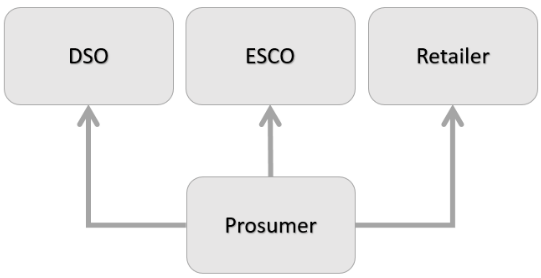


*Figure 1.6. Contractual relations and economic flows with an ESCO*

Indirect control mechanisms can also be used in other contexts, for instance when a **Charging Service Manager** (CSM) sends price signals to PEVs at a charging site, and the PEV drivers decide their charging schedules in response to the prices.

## Flexibility contracts – direct control

**Direct control**, also denoted centralized control, is the mechanism where a central agent remotely controls customers' equipment (Ygge & Ackermans, 1996). Such actions must be done according to a contract (Kostková et al., 2013). Dependent on the case at hand, the central agent can be taken by different market roles. One option is that the DSO itself enters a flexibility contract with the prosumer and performs the control. Another option is that this task is handled by a third party that professionalizes in flexibility services. We denote this role the **Flexibility aggregator** (Eurelectric, 2014; He et al., 2013; Li et al., 2013), since it aggregates many small volumes of flexibility. Flexibility contracts must be entered between the DSO and the Flexibility aggregator on one side, and between the Flexibility aggregator and each of the prosumers on the other. These relationships are illustrated in Figure 1.7.


*Figure 1.7. Contractual relations and economic flows with a flexibility aggregator*

The flexibility aggregator role may be taken by incumbent market roles, like a DSO or a retailer, or by a new market entrant. In some cases, however, the business opportunities may be limited when a DSO takes this role, due to the monopolistic regulation.

With the direct control mechanism flexibility can be activated when needed and at the desired locations in a more targeted way compared to indirect control. It is likely that the prosumers perceive this mechanism as a reward since they are compensated for their flexibility contribution. On the other side, more technology is needed.

Similar to indirect control, the direct control mechanism can also be used in the case of a CSM. Then the CSM decides the charging schedule for each PEV and sends control signals.

The examples above focus on the flexibility needs for the DSO. However, when a flexibility aggregator is in operation, the aggregated flexibility can be sold to different roles, including the market places. Market access is now easier to obtain since the volumes are aggregated and the flexibility aggregator is a professional and legal entity, in contrast to most of the prosumers. Figure 1.8 illustrates a situation where the flexibility aggregator in addition to selling flexibility services to the DSO also sells to the other roles. The producer and retailer may be willing to pay for flexibility to avoid imbalance costs. Sales to the TSO may be relevant for the capacity reservation and reserves markets. Finally, flexibility may be used for the Day-ahead and Intraday markets to profit from price fluctuations.

To motivate for the participation in direct control, incentive based rewarding contracts are necessary. Haring & Andersson (2014) highlight that efficient contracts must be individual rational and incentive compatible. Individual rationality means that the prosumer profits from entering it, while incentive compatibility means that the prosumer gets incentives to reveal his true flexibility costs. To fulfil these requirements, they propose a contract design framework based on non-linear pricing, where capacity reservation and deployment of reserve energy are rewarded separately. Campaigne & Oren (2016) propose a business model based on a "fuse-control paradigm", where an aggregator sells flexibility by imposing capacity constraints for the underlying prosumers or by signalling a capacity threshold above which a penalty will be imposed. In this model, the decision of allocating the available power to separate devices is left to the prosumers. Contracts are entered between the aggregator and the prosumers for a long term, for instance a season, where the aggregator is given the right to curtail consumption with a specified probability.

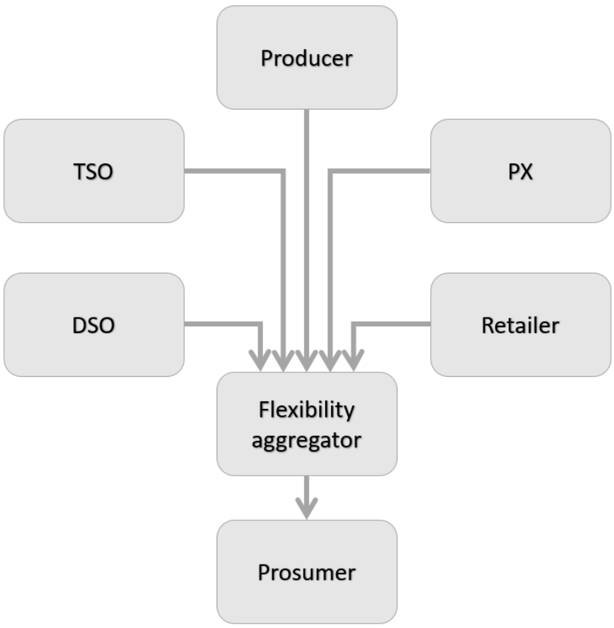


*Figure 1.8. Contractual relations and economic flows a with Flexibility aggregator*

## Flexibility markets

In addition to indirect and direct control contracts, demand side flexibility can be traded in flexibility markets. A review of such markets is given in Eid et al. (2016). They divide into ancillary services, system balancing and network congestion management, spot markets and generation capacity markets. A clearinghouse concept for distribution-level flexibility services, FLECH, is proposed by C. Zhang et al. (2014). The DSO requests a service type for handling overload or voltage problems, aggregators bid their prices and quantities, and the FLECH market runs single-side auctions or super market trading. A bid-less realtime-market is described in Gantenbein et al. (2012). Prices are updated and published every 5 minutes, and smaller units can then respond by changing generation or load (Larsen et al., 2015).

Several R&D and Innovation projects are currently ongoing in this area, for instance evolvDSO[7] (Development of methodologies and tools for new and evolving DSO roles for efficient DRES integration in distribution networks) and EMPOWER[8] (Local electricity retail markets for prosumer Smart Grid power services). The evolvDSO project describes a distribution constraints market where flexibility is contracted and activated in case of local constraints (Puente et al., 2014; Ramos, Puente, & Jackson, 2014). The EMPOWER project proposes local markets for energy, flexibility and other services (Ilieva et al., 2016). Flexibility is here used for several purposes: To handle local imbalances, to handle local grid problems and to sell to wholesale markets.

With the increased dynamics and changed generation and load patterns, there is an increased need for flexibility also at the wholesale level, implying changes in the market designs. Proposed changes include market clearing closer to operation, shorter trading horizons or shorter than one hour trading periods (Barquin, Rouco, & Rivero, 2011), increased cross border trading and innovative reserve products and balancing arrangements (Woodhouse & Keane, 2014).

## Price volatility

Due to more dynamic and unpredictable conditions in the supply and demand situations, market prices will also have a more volatile character (Ketterer, 2014). Figure 1.9 shows large price movements in the German Day-ahead market (Paraschiv, Erni, & Pietsch, 2014). Notice in particular that prices in some periods are negative, which sometimes occurs in situations with large volumes of generation from sun and wind, combined with low load.

[7] www.evolvdso.eu

[8] www.empowerh2020.eu

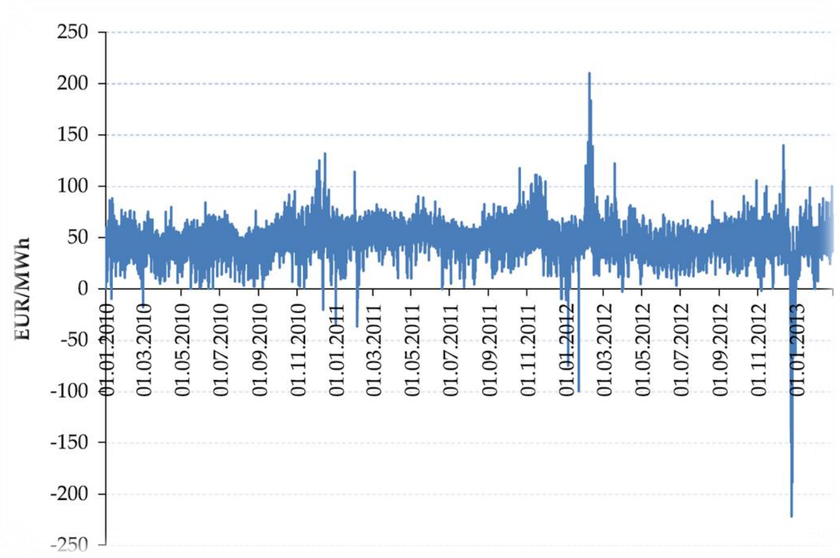


*Figure 1.9. Dynamic and volatile prices*

Making proper price forecasts is therefore an increasingly complex task and of course very important in order to make optimal trading and operational decisions in the market. The literature divides forecasts according to forecasting horizon: short-, medium- and long-term. There is no clear consensus in how to split between the categories, but in general we can say that short term covers forecasts from a few minutes up to a few days ahead, medium-term from a few days to a few months and long-term from a few months to years. A variety of methods exist in the field, each with its strengths and weaknesses. Weron (2014) gives a comprehensive state-of-the-art review and also looks into the future. He classifies the different methods into five groups: multi-agent models, fundamental methods, reduced-form models, statistical approaches and computational intelligence techniques.

# 1.3. Implications to decision support models

The previous section described how demand side flexibility can contribute to creating benefits for different parts of the electricity value chain. Incentives defined in different contract types and at different market places create opportunities to reduce cost or increase profit. To realize these opportunities, the roles that manage the flexibility need proper decision support models. In this thesis we focus on bidding and scheduling decisions. In particular, we are interested in how to model the relation between the technical and economic system efficiently. Further, it is important to take into account that all information is not available in the decision making process. Handling these aspects properly is crucial to make the models applicable to real-life problems.

This section starts with a short introduction to optimization methodology, with focus on the model classes used in this thesis. The description is meant for non-expert readers. For a broader introduction, see text books like Hillier & Lieberman (2010). Next, bidding and scheduling models are described including how technical and economic changes in the electricity value chain have implications to them.

## Optimization methodology

In this thesis we use **Operations Research**[9] (OR) defined as *a discipline that deals with the application of advanced analytical methods to help make better decisions* (Informs, 2016). OR is an interdisciplinary science with no clear cut boundaries. The terms management science and analytics are sometimes used as synonyms for OR. A cornerstone in the theoretical fundament of OR is mathematical programming. In this setting programming should be understood as planning, and the terms program, problem and model is often used interchangeably (Williams, 2013). Mathematical programming deals with problems where one seeks to maximize or minimize a real function by choosing the values of real or integer variables from an allowed set.

[9] Operational research in British English

## Linear Programming

In **Linear Programming** (LP) a linear objective function is optimized over a convex polyhedron specified by linear and non-negativity constraints. Such problems are easy to solve, since the optimal solution always is at the intersection of some constraints, see Dantzig (1949), who was one of the pioneers in the OR field, developing the simplex method for solving LPs.

A general LP can be formulated in the following way:

$$\max c^T x \tag{1.1}$$

$$s.t. Ax \leq b \tag{1.2}$$

$$x \geq 0 \tag{1.3}$$

Here, the decision variables are given by vector *x*, while the vectors $c^T$ and *b* and the matrix *A* contain parameters. Equation (1.1) is the objective function, equations (1.2) and (1.3) define the feasible set for *x*.

## Mixed Integer Linear Programming

In cases where all or some of the variables are required to take an integer value, the model type is called **Integer Programming** (IP) or **Mixed Integer Linear Programming** (MILP), respectively. Many real-life problems include binary variables, which only can take the values 0 or 1.

A general MILP can be formulated in the following way:

$$\max c^T x + d^T y \tag{1.4}$$

$$s.t. Ax + Dy \leq b \tag{1.5}$$

$$x \geq 0 \tag{1.6}$$

$$y \text{ integer} \tag{1.7}$$

The decision variables are *x* and *y*, where *y* is required to be integer. Since a MILP by definition is non-convex, the simplex method can not be used directly. Branch and bound methods and cutting plane techniques are widely applied to solve MILP problems, see for instance Wolsey (2008).

## Quadratic Programming

**Quadratic Programming** (QP) is a special type of non-linear programming, where the objective function is quadratic, while the constraint set is linear. Several special solution algorithms exist for this problem class, one is a modified version of the simplex method (Hillier & Lieberman, 2010).

A general QP can be formulated in the following way:

$$\max c^T x + x^T Q x \tag{1.8}$$

$$s.t. \, Ax \le b \tag{1.9}$$

$$x \ge 0 \tag{1.10}$$

## Stochastic Programming

In many real-world problems some of the parameters may not be known with certainty. Generation from solar panels, electricity demand or electricity prices might be unknown at the time when we need to make a decision. A possible approach is to generate forecasts and make decisions based on these. Such an approach is denoted deterministic and will provide optimal solutions given that the uncertain parameters realize according to the forecasts. It does not consider what happens if they realize differently. **Stochastic Programming** (SP) is a problem class where the uncertainty is explicitly taken into account when solving the problem. SP offers a solution that is more flexible in meeting different outcomes of the uncertain parameters. The literature on stochastic programming goes back to the work by Dantzig (1955). Introductions to the field are for instance given in the textbooks by Kall & Wallace (1994) or Birge & Louveaux (2011), and a tutorial is given by Higle (2005). For applications of stochastic programming to the electricity market, see Conejo, Carrión, & Morales (2010) and Wallace & Fleten (2003). A basic assumption in SP is that the probability distribution of the uncertain parameters is known. A frequently used approach is to discretize the uncertainties in scenario trees, where a scenario represents a possible realization of the uncertain parameters.

An example of a SP is:

$$\max c^T x + \sum_{s \in S} p_s d_s^T y_s \tag{1.11}$$

$$s.t. Ax = b \tag{1.12}$$

$$T_s x + W_s y_s = h_s, \quad s \in S \tag{1.13}$$

$$x \geq 0 \tag{1.14}$$

$$y_s \geq 0, \quad s \in S \tag{1.15}$$

This problem is denoted a 2-stage stochastic problem or recourse problem. The set of scenarios, $S$, represents the discretization of the possible outcomes of the uncertain parameters, and $p_s$ represents their probabilities. The first stage decisions, $x$, are taken before the outcome of the uncertain parameters are known. The second stage or recourse decision, $y_s$, can be adapted to each realized scenario, since they are taken after the uncertainty is revealed.

The left-hand side of Figure 1.10 shows a 2-stage scenario tree with three scenarios. The first-stage decisions are taken in the root node (to the left), while the second-stage decisions are taken in the leaf-nodes (to the right). The problem type can be generalized to multistage stochastic programs, where new information is revealed between the stages and new decisions are made in each stage. The right-hand side of Figure 1.10 shows an example of a three-stage scenario tree. Since a scenario is defined as a path from the root node to a leaf node, the example has 6 scenarios. Note that the first-stage decisions are made before any of the uncertain parameters are known. The second stage decisions are made after the first-stage uncertain parameters are revealed, but the second-stage parameters still are unknown. Finally, the third-stage decisions are made when all uncertainty is revealed.

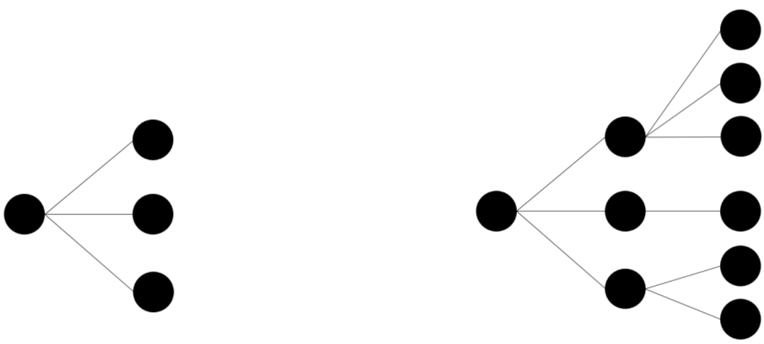

*Figure 1.10. Two-stage (left) and three-stage (right) scenario trees*

## Bidding optimization models

In this section decision support models for bidding problems are described. We start out by defining what a bid is and describe bid formats relevant for this thesis. Then we refer to models for the participants in the traditional value chain and further to implications due to the changes described in section 1.2.

A bid defines a market participant's willingness to purchase or sell a certain volume at a certain price in a certain time interval. We use the term period for a time interval in this thesis. The bidding terminology used in the literature is somewhat confusing, since terms like order, offer and ask also are used, sometimes distinguishing between sale and purchase. To simplify, we use the term bid both for purchase and sale, and for all market types. Different bid formats exist in different markets. In some cases, it is also possible to bid according to several different formats in the same market.

The bids relevant for this thesis can be divided into three categories:

- Piece-wise linear bid curves valid for one period, defined by several pairs of quantity and price with linearization between the pairs, see the left hand side of Figure 1.11
- Step-wise bid curves valid for one period, defined by several pairs of quantity and price with steps between the pairs, see the right hand side of Figure 1.11
- Block-bids, defined by a pair of quantity and price that must be accepted as a whole or not at all for a set of consecutive periods

In addition, several other formats exist, like flexible bids (a volume and a price where the market operator can determine which period(s) it is placed), and several complex types, see for instance the description of bid formats for the price coupling project for PXs in Europe (PCR PXs, 2013).

Since the bids give the market participants the opportunity to bid different volumes to different prices, bidding optimization models are most relevant for participants with elastic demand or dispatchable units. The latter has traditionally been power producers with hydro or thermal power plants, see for instance Fleten & Kristoffersen (2007) and Conejo, Nogales, & Arroyo (2002). The bid decision is taken before the market prices are known. Other parameters may also be uncertain, like precipitation and water inflows in hydro-based systems. Hence, stochastic programming is frequently used for bidding optimization models.

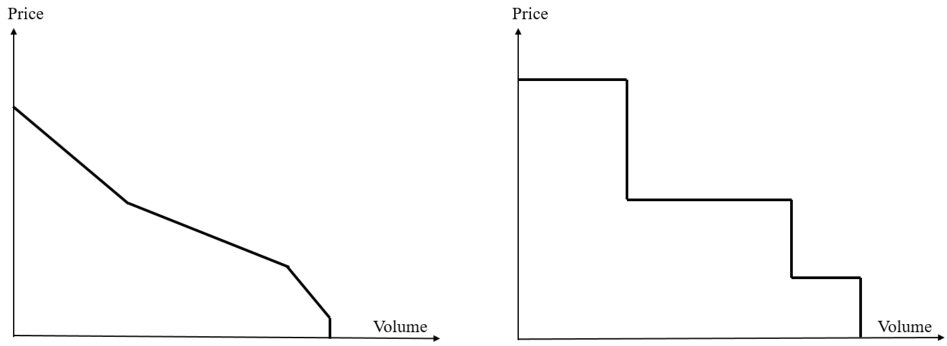


*Figure 1.11. Piece-wise linear and step-wise bid curves for purchase*

For producers without dispatchable units, the problem is to decide the optimal volume, and then bid this for all prices. Such a price-insensitive strategy is denoted flat-bid, and is for instance used by producers with wind parks only. Since the wind speed is uncertain, a central problem is to decide the optimal volume that minimizes the expected imbalance costs that occur due to deviations between committed and produced volumes (Botterud et al., 2012; Matevosyan & Soder, 2006). Other strategies can be to reduce imbalances by trading in the Intra-day market (Morales, Conejo, & Pérez-Ruiz, 2010) or by hedging in financial markets (Hedman & Sheble, 2006). Integrated day-ahead bidding and real-time operating strategies for wind-storage systems are proposed by Ding et al. (2016). The storage system can be used to perform arbitrage and to alleviate wind power deviations from day-ahead commitments.

Flat-bid strategies have also been usual for demand side participants like retailers and larger industrial consumers, due to the lack of dispatchable units and little responsiveness to prices. An early bidding model for a retailer with price-sensitive customers is given in Fleten & Pettersen (2005). Optimal construction of bidding curves for one hour under uncertain load and day-ahead and imbalance prices are obtained by a stochastic linear programming model. A genetic algorithm is used by Herranz et al. (2012) to derive optimal bidding strategies for a retailer supplying electricity to end-users by purchasing in a sequence of day-ahead and intraday markets. Further, a stochastic complementarity model for strategic bidding curves for a large consumer is proposed by Kazempour, Conejo, & Ruiz (2015). All these references cover situations with elastic demand, but do not include dispatchable units.

With the traditional consumer evolving into a prosumer with dispatchable units, more advanced bidding strategies, and therefore more advanced bidding optimization models are needed. The literature in this field covers different market participant types (e.g. a prosumer, a retailer, an aggregator, a microgrid), participation in different markets (e.g. day-ahead + imbalance, day-ahead + intraday) and different modelling approaches (stochastic programming, genetic algorithms, game theory). Further, they include different types of units (load, storage, generation) and different levels of uncertainty (prices, load, generation). However, most of the articles do not cover bidding curves, but decide only the optimal volume and hence, handle flat bid strategies. Some exceptions are referenced below.

Kohansal & Mohsenian-Rad (2016) propose a stochastic MILP to the bidding problem for time-shiftable loads participating in a day-ahead market and where imbalances are penalized in a real time market. The bidding problem for a retailer with self-generation facilities and flexible demands are analysed by Nojavan, Mohammadi-Ivatloo, & Zare (2015). They propose a robust MILP.

The bidding problem of EV aggregators is studied by Vayá & Andersson (2013) who propose a MILP to decide optimal purchase strategies for the charging demand for an EV fleet in a day-ahead market. Market prices and demand are uncertain, but demand is considered flexible in terms of time-shifting. More advanced approaches, like participating in reserves markets including V2G properties, are also frequently studied (Vagropoulos & Bakirtzis, 2013).

A bidding strategy for a microgrid is proposed in Liu, Xu, & Tomsovic (2016). The microgrid participates in a day-ahead market and imbalances are penalized in a real-time market. They include both intermittent and dispatchable DG, storage and price responsive loads. Expected net cost is minimized through a combination of mixed integer stochastic and robust model taking into account uncertain market prices and intermittent generation. Scheduling decisions are made for storage units and the dispatchable DG after prices and commitments are published from the day-ahead market. A similar problem is studied by Ferruzzi et al. (2016), but they use a genetic algorithm to solve the day-ahead bidding problem.

Papers 2 and 3 in this thesis deal with bidding problems. The main contribution from paper 2 is the representation of the bidding process seen from demand side taking into consideration the interrelation between hours and the connection to the underlying physical energy system in the portfolio of prosumers. We model the bidding and scheduling process as a two-stage stochastic program, where uncertain parameters are represented in scenario trees. We illustrate this by including a case study where we also calculate the value of flexibility and the value of stochastic planning for a specific Norwegian case simulated over a two-month period.

In paper 3 we develop a mixed integer multi-stage stochastic programming model for coordinated bidding to determine optimal bidding strategies for a flexibility aggregator participating in three sequential markets, including a market for reservation of capacity. We model explicitly the information revelation process, and take into account that prices may realize differently from the scenarios. To ensure technically feasible solutions, we put effort into modelling the flexibility units properly to capture physical and economic constraints in the underlying, physical systems. Finally, we perform a realistic case-study based on 4 industrial companies and one aggregator including a quantification and discussion of the value of flexibility and the value of aggregation

## Scheduling optimization models

Scheduling is the task to decide operational levels to each dispatchable unit, and is sometimes done after a bidding process, such that the market commitment is split down to individual units. Scheduling may also be done in settings that do not involve bidding, for instance where a retail price is given, where a total microgrid is to be scheduled to minimum cost or in cases with other objectives than cost minimization or profit maximization.

Similar to the bidding problems, the electricity generation is a highly studied topic also when it comes to scheduling. A recent review of scheduling optimization models for generators is given in Zheng, Wang, & Liu (2015).

Since demand-side traditionally has been inflexible, the scheduling problem has not been relevant. With demand-side flexibility this is changing and the topic is now frequently investigated. Also here, authors take different market participant perspectives. For recent reviews of scheduling models, see Haider et al. (2016) regarding residential demand response, Yang, Li, & Foley (2015) regarding EV aggregators and Gu et al. (2014) for microgrid. Since the bidding problems are relevant only in market based and de-regulated frameworks, they often have cost minimization or profit maximization as the objective. The scheduling problems are relevant both in regulated and de-regulated regimes and often cover additional targets like renewable energy utilization maximization, greenhouse gas (GHG) emission minimization, power loss minimization, load variation minimization or different combinations in hybrid models.

Scheduling problems are handled in a wide variety of modelling approaches. Yang et al. (2015) divide the models in mathematical optimization methods, like linear and non-linear programming, quadratic programming, mixed integer programming and dynamic programming, and meta-heuristic approaches like genetic algorithms and particle swarm optimization.

A fundamental issue for scheduling optimization models is how to model the energy system and the flexibility properties. According to economic theory, price responsive demand can be represented by a non-linear price-demand curve. This representation is also used in the demand response context (Albadi & El-Saadany, 2008; Fleten & Pettersen, 2005), but it disregards inter-temporal effects. Another simplified approach was proposed by Conejo, Morales, & Baringo (2010), where a minimum daily electricity consumption for a building must be met, constrained by a minimum and maximum power level. Gatsis & Giannakis (2011) split the load into three categories: Inflexible, shiftable in time and curtailable to a possible dissatisfaction. Several other authors propose to split the loads into appliance types with different typical characteristics and establish mathematical models for each type (Dai & Mesbahi, 2013; S. H. Hong, Yu, & Huang, 2015; Mohsenian-Rad & Leon-Garcia, 2010; Papavasiliou & Oren, 2014; D. Zhang, Shah, & Papageorgiou, 2013). Advantages with such a representation is that it is possible to create control decisions to each appliance and at the same time fulfil technical and comfort related constraints.

Although demand side flexibility is basically related to electricity, increased volumes can be obtained by studying the interrelation between the electrical and thermal energy systems in buildings. A general representation of energy systems in buildings is the Energy hub concept that was initiated at ETH (Geidl et al., 2007). An energy hub is an integrated system where inputs are multiple energy carriers, like electricity, natural gas and district heating. Inside the hub we find appliances for energy production, conversion and storage, like solar panels, wind turbines, water heaters and batteries. Finally, outputs from the energy hub are services to meet certain loads such as electricity, heating and cooling. Bozchalui et al. (2012) and Brahman, Honarmand, & Jadid (2015) apply the energy hub concept in a DR setting.

Figure 1.12 shows a way to group electric appliances in a building. First, they are split into generation, storage and loads units. Next, the load units are divided into inflexible, curtailable and shiftable ones. The figure is an extension of the work by He et al. (2013).

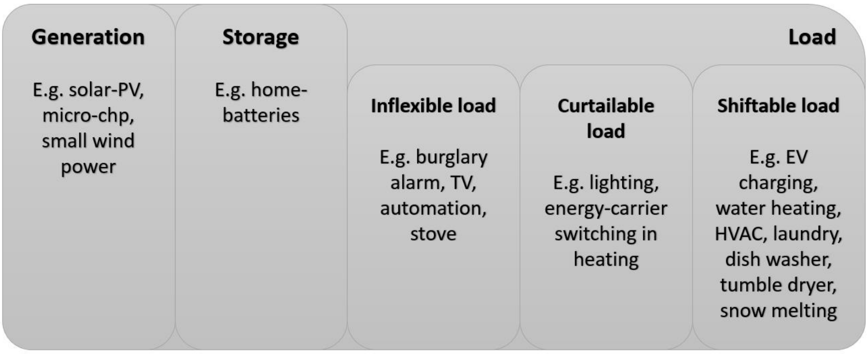


*Figure 1.12. Appliance grouping*

As described earlier, load and generation will be more difficult to forecast and need increased attention, see Figure 1.4. These problems have many similarities with the price forecasting problem regarding forecasting horizons and modelling approaches. However, forecasting of load and generation have the property that aggregated forecasts tend to be better compared to individual. Recent reviews of load forecasting methods are given in T. Hong & Fan (2016), Khan et al. (2016) and Raza & Khosravi (2015), while wind and solar generation forecasting are given in Ren, Suganthan, & Srikanth (2015),Wan et al. (2015) and Widén et al. (2015).

All papers in this thesis deal with scheduling problems. In paper 1 we develop a general and integrated representation of energy systems in buildings covering multiple energy carriers, generation/conversion technologies, storage appliances and electric and thermal loads classified by their flexibility properties. A Facility Manager’s or ESCO’s objective to minimize expected total energy-costs by scheduling flexible appliances is formulated as a stochastic MILP. We handle price models that also includes peak power fees and represent uncertain parameters explicitly. We illustrate this by including a small case-study and discussing the effect of disregarding uncertainty when modeling demand side flexibility.

In papers 2 and 3 we handle the scheduling process as the last, deterministic stage after a bidding process in one (paper 2) and multiple, sequential (paper 3) markets.

In the final paper we propose two different decision support methods for direct control of the charging process scheduling for a CSM. One method requires that the PEV driver shares information with the CSM, while the other does not. The first is optimization based and formulated as a quadratic program, while the other is rule-based. To make the methods applicable in real life, we take into account that the information about arrivals, departures and possibly preferences is revealed gradually. We analyse and compare the performance of each method. As a benchmark, we also analyse a situation with uncontrolled charging and another assuming perfect foresight.

## 1.4. Papers

### Paper 1: A stochastic model for scheduling energy flexibility in buildings

The first paper proposes a decision support model for a Facility Manager or an ESCO to schedule flexible appliances in a building, with the objective to minimize total energy costs. We assume that the building acts as a prosumer participating at the end-user side of the market, with retail prices based on Day-ahead prices and grid contract including power charges. Hence, the prosumer is exposed to indirect control mechanisms. In the paper, we propose a method to classify and model energy units in buildings, covering loads, storages and generation. We combine the energy hub concept with the appliance grouping showed in Figure 1.12 and formulate this mathematically. Flexibility properties are emphasized in the modelling. This constitutes a corner stone in the thesis, since the concept is reused in different ways in the consecutive papers. A stochastic MILP is formulated to capture uncertain load, generation and prices. The paper includes a case study performed in cooperation with Statsbygg.

The paper is published in Energy 88 (2015), pages 364 – 376. Co-author is my supervisor, Professor Asgeir Tomasgard. The research topic was initiated in the project *Manage Smart in Smart Grids*, and the modelling approach was outlined through discussions between me and Professor Tomasgard. I collected data, formulated and implemented the optimization, forecasting and scenario generation models, had discussions with Statsbygg and ran the simulations. Interpretation of the results was done in collaboration with Professor Tomasgard. I was the main author of the manuscript.

### Paper 2: Prosumer bidding and scheduling in electricity markets

In this paper we propose short-term decision-support models for an aggregator that sells electricity to flexible prosumers and buys back surplus electricity. The aggregator then operates as a retailer and a flexibility aggregator and uses direct control mechanism to dispatch the prosumers' equipment. Cost minimization is the aggregator's objective, by making optimal bidding decisions to an electricity spot market, also taking into account costs from grid tariffs, use of fuels and imbalance penalizations. We formulate a two-stage stochastic MILP where the bidding decisions are taken in the first stage and the scheduling in the second. The paper includes a case study performed in cooperation with Smart Energi Hvaler and Norske Skog Saugbrugs.

The paper is published in Energy 94 (2016) pages 828 – 843. Co-authors are Professor Stein-Erik Fleten and my supervisor, Professor Asgeir Tomasgard. The problem definition and the research approach were decided through joint discussions with Professor Fleten and Professor Tomasgard. I collected the data and had discussions with the case partners, formulated and implemented the optimization models and generated the scenarios. The analyses and interpretation of the results were done in collaboration with Professor Fleten and Professor Tomasgard. I was the main author of the manuscript.

## Paper 3: Multi market bidding strategies for demand side flexibility aggregators in electricity markets

In paper 3 we propose a coordinated bidding strategy for a flexibility aggregator's profit maximization problem when trading in three sequential markets. Similar to paper 2, the aggregator uses direct control to dispatch equipment, in this paper at the facilities of flexibility vendors. We formulate the problem as multistage stochastic programs, where market prices are gradually revealed. Bidding decisions to the markets are done in three stages under uncertain prices, while the scheduling decisions are made in the fourth, deterministic stage. The paper includes a case study performed in cooperation with Statkraft and four industrial companies.

The paper is submitted to an international, peer-reviewed journal. Co-authors are Professor Stein-Erik Fleten and my supervisor, Professor Asgeir Tomasgard. The problem definition and the modelling approach were decided through joint discussions with Professor Fleten and Professor Tomasgard. I collected the data and had discussions with Statkraft and the industrial companies, formulated and implemented the optimization models and generated the scenarios. I analysed and interpreted the results in collaboration with Professor Fleten and Professor Tomasgard, and I was the main author of the manuscript.

## Paper 4: Direct control methods for smart electric vehicle charging at grid constrained charging sites

The last paper proposes two different methods for a CSM that delivers charging services under grid capacity limitations. The CSM uses direct control of the charging power to the PEVs and for the charging and discharging of separate battery banks at the charging site. The CSM's objective is to meet the drivers' charging preferences as much as possible without violating the capacity limits. One method is rule-based and requires no information exchange between the PEV driver and the CSM, while the other is optimization-based and requires information about the drivers' preferences regarding charging demand and time to departure. The optimization model is formulated as a quadric program. A case study is performed in cooperation with Fortum Charge & Drive to analyse the two methods and compare their performances.

The paper is submitted to an international journal. Co-authors are my co-supervisor, Professor Magnus Korpås and my supervisor, Professor Asgeir Tomasgard. The problem formulation was initiated based on an idea from the *ChargeFlex* project and detailed through discussions with Professor Korpås and Professor Tomasgard. Likewise, the two direct control mechanism proposals were jointly discussed and decided. Then I collected the data and had discussions with Fortum Charge and Drive, formulated and implemented the models. I analysed and interpreted the results in collaboration with Professor Korpås and Professor Tomasgard and I was the main author of the manuscript.

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Paper 1

Stig Ødegaard Ottesen and Asgeir Tomasgard:

# *A stochastic model for scheduling energy flexibility in buildings*

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# Chapter 2. A stochastic model for scheduling energy flexibility in buildings


## Abstract

Due to technological developments and political goals, the electricity system is undergoing significant changes, and a more active demand side is needed. In this paper, we propose a new model to support the scheduling process for energy flexibility in buildings. We have selected an integrated energy carrier approach based on the energy hub concept, which captures multiple energy carriers, converters and storages to increase the flexibility potential. Furthermore, we propose a general classification of load units according to their flexibility properties. Finally, we define price structures that include both time-varying prices and peak power fees. We demonstrate the properties of the model in a case study based on a Norwegian university college building. The study shows that the model is able to reduce costs by reducing peak loads and utilizing price differences between periods and energy carriers. We illustrate and discuss the properties of two different approaches to deal with uncertain parameters: Rolling horizon deterministic planning and rolling horizon stochastic planning, the latter includes explicit modeling of the uncertain parameters. Although in our limited case, the stochastic model does not outperform the deterministic model, our findings indicate that several factors influence this conclusion. We recommend an in-depth analysis in each specific case.

## 2.1. Introduction

According to the IEA (International Energy Agency, 2008), demand side activities should be the first choice in all energy policy decisions that aim to create more reliable and sustainable energy systems. Demand side activities integrated with smart grid technologies (International Energy Agency, 2011) represent a wide variety of benefits for different stakeholders in the energy value chain and society as a whole. Examples are: cost reductions for consumers, increased ability to integrate intermittent renewable power generation and electric vehicles, improved energy system reliability and less costly network reinforcements (Giordano et al., 2012; Siano, 2014; US Department of Energy, 2006; Wakefield, 2010). Many studies quantify the potential benefits from demand side activities (Alcázar-Ortega et al., 2012; Capgemini, 2008; Cappers, Goldman, & Kathan, 2010; Saele & Grande, 2011; The Brattle Group, 2007) with respect to reductions in cost, peak demand and emissions. In this paper we will present a decision-support model that can be used to control the demand side flexibility in a building.

A price elastic inverse demand curve is a simplified representation of flexible demand (Albadi & El-Saadany, 2008; Fleten & Pettersen, 2005). This representation is not sufficient to describe demand response, as it lacks an explicit link to the underlying physical energy system and thereby also an inter-relation between time periods. It disregards the fact that changing the load in one period may affect demand and the feasible decision space in later periods. Several authors have addressed demand response in short-term multi-period optimization models. Conejo et al. (Conejo, Morales, & Baringo, 2010) introduce a real-time electricity demand response model for a household or a small business where a minimum daily energy-consumption level must be met, constrained by maximum and minimum hourly load levels. Gatsis & Giannakis (2011) split the load of a residence into three components: one "must-run", one adjustable where the total amount must be met over the scheduling horizon and finally one that can be reduced, but at the dissatisfaction of the end-user. In Mohsenian-Rad & Leon-Garcia (2010) and Papavasiliou & Oren (2014) the concept of deferrable loads is introduced with limits for start- and end-time in addition to minimum and maximum load levels and total load. A combination of the above-mentioned concepts is presented by Hong, Yu, & Huang (2015), who describe an approach to allocate load among individual appliances. Loads are categorized into non-shiftable, shiftable and controllable. In addition to reducing cost by shifting loads from high-price to low-price hours, their model seeks to reduce the number of peak demand hours. Finally, Zhang, Shah, & Papageorgiou (2013) and Dai & Mesbahi (2013) take into consideration that some types of loads cannot be interrupted or changed when first started. In real life, different appliances will fit into variations of the above representations.

Our main contribution is to synthesize these different load classes into an integrated model of the building energy system. While the articles above focus on electricity only, we also capture the possible interaction between the electric and thermal appliances, and this increases the flexibility potential. Granado, Wallace, & Pang (2014) is an example of a paper that includes both electric and heat loads. Moreover, they cover self-generation of electricity and heat from several energy carriers. Their target is to quantify the value of electricity storage. However, they do not include flexible loads or interaction between the heating and electric appliances in the building.

Interaction between electricity and heat is covered by many articles focusing on the scheduling of combined heat and power facilities. For instance, Mitra, Sun, & Grossmann (2013) present a detailed model covering all technical constraints for co-generating units, including fuel switching and the possibility to sell surplus electricity to the market. Alipour, Zare, & Mohammadi-Ivatloo (2014) in addition cover power-only generators, heat storage and demand response in terms of shiftable load. However, the load is represented at an aggregated level for the customers. A general representation of energy systems in buildings is the "Energy hub concept" that was initiated at ETH (Geidl et al., 2007). An energy hub is an integrated system where inputs are multiple energy carriers, like electricity, natural gas and district heating. Inside the hub we find appliances for energy production, conversion and storage, like solar panels, wind turbines, water heaters and batteries. Finally, outputs from the energy hub are services to meet certain loads such as electricity, heating and cooling. Bozchalui et al. (2012) and Brahman, Honarmand, & Jadid (2015) apply the energy hub concept on smart grid and demand response. These papers focus specifically on residential buildings, while we want to develop a model that can also capture other types of buildings and appliances.

The papers referenced above all base their price model on the concept of time-differentiated prices. Several such price models exist, denoted day-ahead pricing, real-time pricing, time-of-use pricing and critical peak pricing, to mention a few. For an overview of time-differentiated price models, see Albadi & El-Saadany (2008), Borenstein, Jaske, & Rosenfeld (2002) Griffin & Puller (2009) or Schweppe et al. (1988). Other price models differentiate between consumption level, denoted progressive power tariffs, like inclining block rates (Mohsenian-Rad & Leon-Garcia, 2010) or subscribed power (Sæle et al., 2015), where the marginal price increases with the quantity consumed. Furthermore, some price models include a peak power fee, sometimes denoted demand charge (Pacific Power, 2015), where the contract contains an element to be paid based on metered maximum hourly or quarterly power out-take over a certain period. For example, all Nordic buildings above a given size have some kind of peak power fee. Due to increased dynamics from fluctuating renewable energy generation, charging of electric vehicles and other types of demand, the focus on price models that penalizes load peaks is expected to increase (Puchegger, 2015). We take this into consideration in the scheduling decision process. This issue is disregarded in the papers mentioned above.

An additional challenge with the peak power fee is that we do not know upfront what time the peak load will occur or its magnitude. In general, all load values for the scheduling horizon are uncertain. The referenced papers above disregard this fact. Furthermore, if our problem contains generation from sources like solar or wind, these values will also be uncertain. Finally, the electricity prices may be uncertain at the time we make the scheduling decisions. In this paper we propose a model that considers that some parameters may be uncertain when making the scheduling decisions and analyze the effect from disregarding this uncertainty.

The contribution from this article is three-fold:

- A general and integrated representation of energy systems in buildings covering multiple energy carriers, generation/conversion technologies, storage appliances and electric and thermal loads classified by their flexibility properties
- A price model that also includes peak power fees
- Explicit representation of uncertain parameters

We illustrate this by including a small case-study and discussing the effect of disregarding uncertainty when modeling demand side flexibility.

The remainder of this paper is organized as follows: in Section 2.2 we describe how to model the internal energy systems and load flexibility classes. The scheduling problem and the mathematical formulation are described in Section 2.3. We document and present results from a case study in Section 2.4.

## 2.2. Internal energy system modelling

We base our model for the energy system in a building on a further development of the energy hub concept (Geidl et al., 2007) and introduce the notion of an internal energy system. A building can have one or multiple internal energy systems, each consisting of converter units that convert one energy carrier to another. Examples include: electricity to hot water, gas to electricity and wind to electricity. Each internal energy system has a specific energy carrier that serves loads, e.g. electricity specific loads (PCs, lights, fans), hot water specific loads (space heating and tap water) and cooling specific loads (cooling server rooms). We include conversion technologies as intermittent energy generation from energy sources like the sun and wind. For the sake of generality, we will use the term energy carrier also for input to these. Conversion units generating electricity based on intermittent energy are not dispatchable. Units that are dispatchable are constrained by ramping limits, minimum up-time when started and minimum down-time when stopped, efficiency parameters and maximum levels.

We model direct connection as a special type of converter, where the energy carrier is imported into an internal energy system without conversion. In general, an energy carrier can also be exported from the building through a direct connection. We also allow one or multiple storage units in each of the internal energy systems. Storage units may represent appliances like electric batteries or hot water tanks. Storages are parameterized with volumes, maximum charging and discharging capacities and related efficiency factors. Finally, each internal energy system may have several load units. These may be a physical appliance, a group of physical appliances or a virtual component, like a room.

We base the load unit class definitions on a synthesis of the concepts described in the introduction. We choose to split into two shiftable (in time) load types, two curtailable load types and one inflexible load type.

For **Shiftable load units** the total load must always be met, but it may be moved within a given time interval. Examples of load shifting units are washing and drying processes where the choice of operating period is not critical, as long as the process is ready by a deadline. Charging of batteries for electric vehicles is another example. Within this class we further distinguish between **Shiftable profile load units** (that can be moved, but where the energy profile cannot be changed) and **Shiftable volume load units** (where the total volume must be met over a set of time periods, but the profile can change within limits).

For **Curtailable load units** the load may be reduced without being replaced, at a possible disutility (loss of comfort, loss of income or added costs) for the user. Examples are stopping industrial processes or dimming lights. We distinguish between **Reducible load units** where the load can be reduced down to a certain level without switching off, and **Disconnectable load units**, where the unit is either on or completely off. Rules and parameters regulate allowable curtailment periods, maximum curtailment duration, maximum number of curtailments and minimum duration between two curtailments.

Figure 2.1 illustrates how the different load flexibility classes work. Figure 2.1.A shows the original forecasted load, while the other four figures give examples of a feasible schedule for each of the different flexible load unit types. The *x*-axis represents time periods while the *y*-axis represents the energy level. In Figure 2.1.B (shiftable profile) the load is delayed for three periods. In Figure 2.1.C (shiftable volume) the total volume is met, but in different periods and with a different profile. A load reduction in period 4 is shown in Figure 2.1.D, while disconnection in period 4 is shown in Figure 2.1.E.

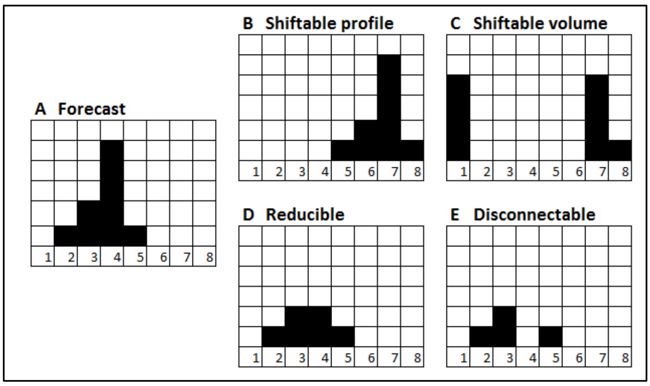



*Figure 2.1. Illustration of the different load flexibility classes*

The **inflexible load unit** class covers all load units where load must be met under any circumstance. Electricity to cooking appliances and televisions are examples. The schedule for such units will be equal to the forecast.

Figure 2.2 illustrates the total technology model for a building, where we have three different external energy carriers that are fed into five converter units in two internal energy systems. Each internal energy system also has three storages and three load units.

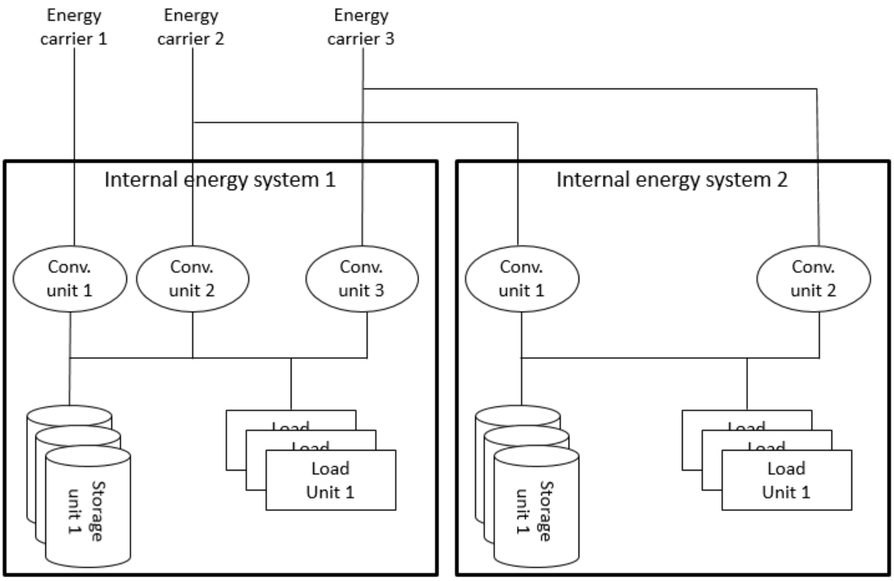



*Figure 2.2. Illustration of the total technology model*

## 2.3. The scheduling problem and the mathematical formulation

In this paper we want to decide the optimal plan for the utilization of flexible units. The plan covers several periods within a planning horizon. We denote this as the scheduling problem. In this section we formulate the mathematical model as a two-stage stochastic recourse program (Kall & Wallace, 1994). The parameters and variables are described successively as they appear. A full list is found in Appendix 2.A.

### Uncertainty and information structure

Borenstein et al. (2002) describe two different aspects that must be taken into consideration for retail pricing regimes: 1) The granularity of prices, i.e. the frequency with which prices change within the day or week and 2) The timeliness of prices, i.e. the time lag between when a price is set and when it is actually effective. In our model we define a general term period, which for retail electricity markets typically will be one hour. Finer time resolutions can be used, but may require more detailed models of the internal energy systems. Prices may not be known at the time we decide the schedule. To keep generality we model electricity prices according to a three-part tariff structure including 1) a fixed fee to be paid regardless of amount used, 2) an energy fee depending on the amount of energy used (e.g. time-varying price per kWh), 3) a peak power fee depending on the maximum outtake. The different energy carriers may have different price structures. Intermittent renewable sources have zero cost while most fuel-based carriers will have only energy-related cost components. Electricity and district heating may have all three terms in the price structure.

Also load, solar radiation and wind speed are examples of uncertain variables. The real values will not be known for certain until after the period is over. The quality of forecasts often improves the closer we come to the operations, but in many processes there is natural variation and perfect forecasts are impossible. Often the scheduling process is executed several times a day according to a rolling planning horizon, each time with more certain data for a given period.

An alternative approach is to model the uncertain parameters explicitly. We represent the uncertain parameters by discrete probability distributions in a two-stage scenario tree, as illustrated in Figure 2.3. Two-stage scenario tree with seven scenarios We have a 24 hours' planning horizon which is split into two stages between hours 12 and 13. All information is assumed known with certainty for the first stage, whereas some information is uncertain for the second. Each path through the tree is called a scenario and represents a possible realization of all the uncertain parameters for all periods. We assign a probability to each scenario. If load is the only uncertain parameter, as in our case study, then each scenario contains a possible load curve for the periods from hours 13 to 24, see Figure 2.9. The branching point in the tree (end of hour 12) represents the start of the second stage, when we receive information about which scenario that was realized. The point here is that when we make the scheduling decisions for stage 1, we take into account the different possible outcomes in stage 2. The schedules for stage 1-periods will be equal for all scenarios, while the second stage schedules can vary for the different scenarios. When we enter stage 2, we implement the decisions for the realized scenario. We call the process of alternation decisions and uncertainty revelation, the information structure of the decision problem.

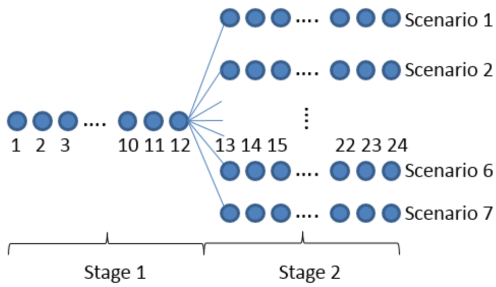



*Figure 2.3. Two-stage scenario tree with seven scenarios*

## Objective function

The objective function minimizing total costs consists of five elements as formulated in Equation (2.1):

$$\min \sum_{s\in S} R_s \cdot \left[ \begin{array}{l} \sum_{a\in A}\sum_{t\in T} P^{energy}_{a,t,s}\,\chi^{import}_{a,t,s} + \sum_{a\in A} P^{peak}_{a}\,\chi^{peak}_{a,s} + \sum_{o\in O}\sum_{y\in Y}\sum_{t\in T} G^{startup}_{o,y}\,\alpha^{start}_{o,y,t,s} + \\ \sum_{d\in D^C}\sum_{y\in Y}\sum_{t\in T} X_{d,y}\,\varphi_{d,y,t,s} - \sum_{a\in A}\sum_{t\in T} P^{sales}_{a,t}\,\chi^{export}_{a,t,s} \end{array} \right] \tag{2.1}$$

where $R_s$ is the probability of scenario $s$. All parameters and variables that may be uncertain have a scenario index, since they are scenario dependent. Note that we can use the formulation also in deterministic cases, where all information is known with certainty. Then we will only have one scenario.

The first element in the objective function is the energy fee, where the energy price $P_{a,t,s}^{energy}$ for energy carrier *a* in time period *t* in scenario *s*, is multiplied with the net import $\chi_{a,t,s}^{import}$ of energy carrier *a*. Next, the peak costs consist of the peak power price $P_a^{peak}$ for energy carrier *a* multiplied with the volume for the peak power fee $\chi_{a,s}^{peak}$. In the third element startup costs for converter units are calculated by multiplying the startup cost $G_{o,y}^{startup}$ for converter *o* in internal energy system *y* with the binary variable $\alpha_{o,y,t,s}^{start}$ which is set to 1 in the period the converter is started up. Disutility for curtailment of load is calculated by multiplying the disutility cost $X_{d,y}$ with the reduced amount $\varphi_{d,y,t,s}$ for curtailable load unit *d*. Last, income from sales of surplus energy is the sum of sales price $P_{a,t}^{sales}$ for energy carrier *a* multiplied with the net export of energy $\chi_{a,t,s}^{export}$ over all time periods and energy carriers.

## Energy carrier constraints

The total import of energy carrier *a*, $\chi_{a,y,o,t,s}$, summed over all converters *o* and internal energy systems *y* must be below the upper capacity limit $U_a$:

$$\sum_{y\in Y}\sum_{o\in O}\chi_{a,y,o,t,s} \le U_a, \qquad a\in A, t\in T, s\in S. \tag{2.2}$$

Equation (2.2) will for instance be used in cases where the sum of electricity power out-take from the grid must be below main fuse size or a contracted maximum power.

Net import and export of energy carrier *a* in period *t* is defined as:

$$\chi_{a,t,s}^{import} = \max((\sum_{y\in Y}\sum_{o\in O}\chi_{a,y,o,t,s}),0), \qquad a\in A, t\in T, s\in S, \tag{2.3}$$

$$\chi_{a,t,s}^{export} = -\min((\sum_{y\in Y}\sum_{o\in O}\chi_{a,y,o,t,s}),0), \qquad a\in A, t\in T, s\in S, \tag{2.4}$$

where $\chi_{a,y,o,t,s}$ is free for converters that can operate in both directions, $o\in O^{2w}$, else non-negative.

Equations (2.3) and (2.4) are needed for variables in the objective function (2.1). Assume that energy carrier 2 in Figure 2.2 is electricity. Then (2.3) will calculate the net out-take of electricity from the grid as the sum of input to converter unit 2 in energy system 1 and to converter unit 1 in energy system 2. If this value is negative, which means that we are exporting surplus electricity, equation (2.3) will return 0. (2.4) will then return a positive value for the export $\chi_{a,t,s}^{export}$.

In situations where the peak power fee is based on a pre-agreed maximum amount, for instance a contracted peak power, we will have:

$$\chi_{a,s}^{peak} = U_a, \qquad a \in A, s \in S. \tag{2.5}$$

If, on the other hand, the peak power fee is based on a maximum used amount, we have:

$$\chi_{a,s}^{peak} = \chi_{a,s}^{max} = \max(\sum_{y \in Y} \sum_{o \in O} \chi_{a,y,o,t,s}), \qquad a \in A,\ s \in S. \tag{2.6}$$

Here we sum the net energy import for each period in the planning horizon and pick the largest value. We do this for each energy carrier.

In this situation it is necessary to include a constraint limiting the peak cost from below to $M_a$, the highest imported volume seen so far in the time interval of the fee calculation:

$$\chi_{a,s}^{max} \geq M_a, \qquad a \in A, s \in S. \tag{2.7}$$

Equation (2.7) is needed for instance in situations where we decide a schedule for one single day, but where the peak power fee is based on a monthly maximum value. Assume we make schedules for a day late in a month. For the earlier days in the same month, we will have a preliminary peak, and we know that the peak fee for the month will at least be based on this value. Then there is no gain in reducing the peak for the scheduling day to a value below the preliminary peak.

## Load unit constraints

### Shiftable load units

For shiftable volume load unit *d* in energy system *y*, we define load shift time intervals $g \in G(d,y)$ defined with a start period $T_g^{start}$ and an end period $T_g^{end}$.

For each load shift interval $g$, the planned sum of energy amount $\omega_{d,y,t,s}$ delivered to shiftable volume load unit *d* over the interval must equal the sum of load forecast $W_{d,y,t,s}$:

$$\sum_{t=T_g^{start}}^{T_g^{end}} \omega_{d,y,t,s} = \sum_{t=T_g^{start}}^{T_g^{end}} W_{d,y,t,s}, \qquad g \in G(d,y),\ s \in S. \tag{2.8}$$

If we look at charging a battery in an electric vehicle, (2.8) will ensure that the scheduled charging summed over all periods (left-hand side) equals the forecasted charging need.

Energy amount $\omega_{d,y,t,s}$ delivered to shiftable volume load unit *d* must be between minimum $E_{d,y}^{min}$ and maximum power limit $E_{d,y}^{max}$:

$$E_{d,y}^{min} \le \omega_{d,y,t,s} \le E_{d,y}^{max}, \quad t \in T^g,\ g \in G(d,y),\ s \in S. \tag{2.9}$$

For shiftable profile load units we introduce the binary decision variable $\gamma_{g,i,s}$ which is set to 1 if the load is shifted *i* periods. Exactly one shifting option must be selected for each shiftable profile load unit in load shift time interval *g*:

$$\sum_{i=T_g^{start}-V_g^{start}}^{T_g^{end}-V_g^{end}} \gamma_{g,i,s} = 1, \qquad g \in G(d,y),\ s \in S. \tag{2.10}$$

Here $T_g^{start}$ and $T_g^{end}$ are respectively the earliest start and latest end for the load shift interval, while $V_g^{start}$ and $V_g^{end}$ are first and last period for the load forecast. We illustrate this in a small example where we have a load forecast for a shiftable profile load unit for periods 9, 10 and 11, see Figure 2.. Then $V^{start} = 9$, while $V^{end} = 11$. Earliest possible start $T^{start} = 7$ and latest possible end $T^{end} = 14$. Two options exist to shift the load backwards ($i =$-1 or -2 periods) and three options to shift the load forward ($i = 1$, 2 or 3 periods). The last option is to keep the load profile as is ($i = 0$). Hence binary variables are defined in the range of *i*, $\gamma_{g,-2,s}$ to $\gamma_{g,+3,s}$.

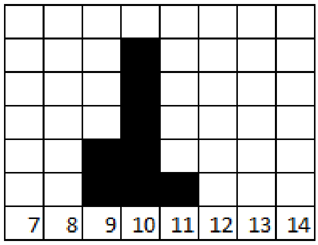



*Figure 2.4. Illustration of a shiftable profile load*

If the decision is for example to shift two periods back, $W_9$ will be assigned to period 7 $(\omega_7 = W_9)$, $W_{10}$ will be assigned to period 8 ($\omega_8 = W_{10}$) and $W_{11}$ will be assigned to period 9 $(\omega_9 = W_{11})$. Hence, we end up with the following equations:

$$\begin{aligned}
&\omega_7 = \gamma_{-2} \cdot W_9, \\
&\omega_8 = \gamma_{-1} \cdot W_9 + \gamma_{-2} \cdot W_{10} \\
&\omega_9 = \gamma_0 \cdot W_9 + \gamma_{-1} \cdot W_{10} + \gamma_{-2} \cdot W_{11} \\
&\omega_{10} = \gamma_1 \cdot W_9 + \gamma_0 \cdot W_{10} + \gamma_{-1} \cdot W_{11} \\
&\omega_{11} = \gamma_2 \cdot W_9 + \gamma_1 \cdot W_{10} + \gamma_0 \cdot W_{11} \\
&\omega_{12} = \gamma_3 \cdot W_9 + \gamma_2 \cdot W_{10} + \gamma_1 \cdot W_{11} \\
&\omega_{13} = \gamma_3 \cdot W_{10} + \gamma_2 \cdot W_{11} \\
&\omega_{14} = \gamma_3 \cdot W_{11}
\end{aligned} \tag{2.11}$$

In order to generalize we introduce a counter *n* going from 0 to $T^{end} - T^{start}$ (in our example from 0 to 7). The delivered energy $\omega_{d,y,t,s}$ to load unit *d* in time period *t* in scenario *s* is then determined by:

$$\omega_{d,y,t,s} = \sum_{n=0}^{T_g^{end} - T_g^{start}} \gamma_{g,(t-T^{start}-n),s} W_{d,y,(T^{start}+n),s}, \quad t \in \left\{T_g^{start}, T_g^{end}\right\}, g \in G(d,y), s \in S \tag{2.12}$$

This formulation includes $\gamma$ variables outside the feasible shift range $\left\{ \mathrm{T}_g^{start} - V_g^{start}, ...., \mathrm{T}_g^{end} - V_g^{end} \right\}$,

so we have to restrict these:

$$\gamma_{g,i,s} = 0,\ i \in \left\{ i \le \mathrm{T}_g^{\,start} - V_g^{\,start} \vee i \ge \mathrm{T}_g^{\,end} - V_g^{\,end} \right\},\ \ g \in G(d,y),\ s \in S. \tag{2.13}$$

## Curtailable load units

We introduce binary variables to control the curtailments. First, $\delta^{start}_{d,y,t,s}$ gets the value 1 in periods where curtailment is started up in the beginning of the period. Second, $\delta^{end}_{d,y,t,s}$ gets the value 1 in periods where curtailment is stopped in the end of the period. Finally, $\delta^{run}_{d,y,t,s}$ gets the value 1 in periods where curtailment is ongoing, but not started or stopped in the same period.

By this definition curtailment cannot start and run in the same time period or run and end in the same period, respectively (but by this definition it can start and end in the same period):

$$\delta^{start}_{d,y,t,s} + \delta^{run}_{d,y,t,s} \le 1, \quad d \in D^C, y \in Y, t \in Z, s \in S, \tag{2.14}$$

$$\delta^{run}_{d,y,t,s} + \delta^{end}_{d,y,t,s} \le 1, \quad d \in D^C, y \in Y, t \in Z, s \in S. \tag{2.15}$$

If a load curtailment starts or runs in a period, it must either run or end in the next period:

$$\delta^{start}_{d,y,t,s} + \delta^{run}_{d,y,t,s} = \delta^{run}_{d,y,t+1,s} + \delta^{end}_{d,y,t+1,s}, \quad d \in D^C, y \in Y, t \in Z, s \in S. \tag{2.16}$$

Curtailment cannot start, run or end in periods where curtailment is not permitted:

$$\delta^{start}_{d,y,t,s} = \delta^{run}_{d,y,t,s} = \delta^{end}_{d,y,t,s} = 0, \quad d \in D^C, y \in Y, t \notin Z, s \in S. \tag{2.17}$$

For the load units that can be curtailed, we limit the duration to $D^{\max}_{d,y}$ periods:

$$\sum_{i=t}^{t+D^{max}_{d,y}-1} \delta^{end}_{d,y,i,s} \ge \delta^{start}_{d,y,t,s}, \quad d \in D^C,\ y \in Y,\ t \in Z,\ s \in S. \tag{2.18}$$

The number of load curtailments must be constrained by the maximum allowable number of curtailments $B^{max}_{d,y}$:

$$\sum_{t \in Z} \delta^{start}_{d,y,t,s} \le B^{max}_{d,y}, \qquad d \in D^C, y \in Y, s \in S. \tag{2.19}$$

A minimum duration $D^{\min}_{d,y}$ must exist between two load curtailments:

$$\delta^{end}_{d,y,t,s} + \sum_{i=t}^{t+D^{min}_{d,y}} \delta^{start}_{d,y,i,s} \leq 1\ , d \in D^{C}, y \in Y, t \in Z, s \in S. \qquad (2.20)$$

We illustrate Equations (2.14) to (2.20) by a small example in Table 2.1. Here a curtailable load unit is curtailed twice: from periods 1 to 3 and from periods 6 to 9:

*Table 2.1. Example of feasible values for the delta-variables*

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| $\delta_t^{start}$ | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| $\delta_t^{run}$ | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 0 |
| $\delta_t^{end}$ | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 |

Since the curtailment starts in period 1, we have $\delta_1^{start} = 1$. Equation (2.14) then forces $\delta_1^{run}$ to be 0. In period 2, (2.15) ensures that maximum one of the variables $\delta_2^{run}$ and $\delta_2^{end}$ get the value 1. Since $\delta_1^{start} = 1$, (2.16) will force one and only one of the variables $\delta_2^{run}$ and $\delta_2^{end}$ to be 1. Since $\delta_2^{run} = 1$, (2.16) requires one and only one of $\delta_3^{run}$ and $\delta_3^{end}$ to be 1.

Assume that the load unit can be curtailed for maximum three periods if curtailed, and that a rest time of minimum two periods must exist between two curtailments. Further, we are allowed to curtail the load unit only twice. The first curtailment starts in the first period (t=1). Equation (2.18) will ensure that $\delta_t^{end}$ must be 1 in one of periods 1, 2 or 3 (since $t+D^{max}-1=1+3-1=3$), and consequently the latest end is in period 3. If the curtailment ends in period 3, the earliest possible restart is in period 6. This is ensured by Equation (2.20). Now t=3 and consequently $\delta_t^{end}$ =1 for t=3. Then $\delta_t^{start}$ must be 0 for t=3, 4 and 5 (since $t+D^{min}=3+2=5$). Furthermore, Equation (2.19) ensures that the number of curtailments is equal to or smaller than 2. In our case, the left-hand side of the equation will be 2, since the $\delta^{start}$ equals 1 for period 1 and 6.

Reduced volume $\varphi_{d,y,t,s}$ can only have a non-zero value in periods where reduction starts, is running or ends. The reduced volume must be constrained by the maximum reducible fraction $U^{\max}_{d,y}$ times the forecast $W_{d,y,t}$:

$$\varphi_{d,y,t,s} \leq U^{\max}_{d,y} W_{d,y,t} \min((\delta^{start}_{d,y,t,s} + \delta^{run}_{d,y,t,s} + \delta^{end}_{d,y,t,s}),1), \qquad d \in D^{CR}, y \in Y, t \in Z, s \in S, \qquad (2.21)$$

which means that we can only reduce volume in periods where one of the deltas have the value 1, see Table 2.1. The "min"-formulation is needed for periods where curtailment is started and stopped in the same period, since then both $\delta^{start}$ and $\delta^{end}$ have the value 1 for the same period.

Disconnectable load units can only be on or off, hence the reduced volume must be either 0 or equal to the total forecast $W_{d,y,t}$:

$$\varphi_{d,y,t,s} = W_{d,y,t} \cdot \min((\delta^{start}_{d,y,t,s} + \delta^{run}_{d,y,t,s} + \delta^{end}_{d,y,t,s}),1), \quad d \in D^{CD}, y \in Y, t \in Z, s \in S. \tag{2.22}$$

## Energy converter unit constraints

For energy converter unit *o* we define the relation between input $\chi_{a,y,o,t,s}$ and output $\psi_{o,y,t,s}$ in the following way:

$$\psi_{o,y,t,s} = A_{o,y} \cdot \chi_{a,y,o,t,s}, \quad o \in O, y \in Y, t \in T, s \in S, \tag{2.23}$$

where $A_{o,y}$ is the efficiency factor. As a simplification we assume this to be a constant factor, not a function. Converter unit *o* cannot start and be running in the same period or run and end in the same period:

$$\alpha^{start}_{o,y,t,s} + \alpha^{run}_{o,y,t,s} \leq 1, \quad o \in O, y \in Y, t \in T, s \in S, \tag{2.24}$$

$$\alpha^{run}_{o,y,t,s} + \alpha^{end}_{o,y,t,s} \leq 1, \quad o \in O, y \in Y, t \in T, s \in S. \tag{2.25}$$

If a converter unit *o* starts or runs in a period, it must either run or end in the next period:

$$\alpha^{start}_{o,y,t,s} + \alpha^{run}_{o,y,t,s} = \alpha^{run}_{o,y,t+1,s} + \alpha^{end}_{o,y,t+1,s}, \quad o \in O, y \in Y, t \in T, s \in S. \tag{2.26}$$

For an illustration of Equations (2.24) to (2.26), see examples for curtailable load units and the explanation of Equations (2.14) to (2.16).

In periods where the converter is in operation, the amount of energy output $\psi_{o,y,t,s}$ must be between minimum $G^{min}_{o,y}$ and maximum $G^{max}_{o,y}$ output, else 0:

$$\min((\alpha_{o,y,t,s}^{start}+\alpha_{o,y,t,s}^{run}+\alpha_{o,y,t,s}^{end}),1)G_{o,y}^{max}\geq\psi_{y,o,t,s}\geq\min((\alpha_{o,y,t,s}^{start}+\alpha_{o,y,t,s}^{run}+\alpha_{o,y,t,s}^{end}),1)G_{o,y}^{min},\quad o\in O,y\in Y,t\in T,s\in S. \tag{2.27}$$

Between period *t* and *t+1* the change of energy output $\psi_{o,y,t,s}$ for converter unit *o* must be between ramping limits $C_{o,y}^{ramp-up}$ and $C_{o,y}^{ramp-down}$:

$$\psi_{o,y,t-1,s}+C_{o,y}^{ramp-up}\geq\psi_{o,y,t,s}\geq\psi_{o,y,t-1,s}-C_{o,y}^{ramp-down},\quad o\in O,y\in Y,t\in T,s\in S. \tag{2.28}$$

When started, there must be a minimum running time $J_{o,y}^{\min-up}$ for converter unit *o*:

$$\alpha_{o,y,t,s}^{start}+\sum_{i=t}^{t+J_{o,y}^{min\text{-}up}-2}\alpha_{o,y,i,s}^{end}\leq 1,\quad o\in O,y\in Y,t\in T,s\in S. \tag{2.29}$$

Similarly, a minimum duration $J_{o,y}^{min\text{-}down}$ must exist between two operations:

$$\alpha_{o,y,t,s}^{end}+\sum_{i=t}^{t+J_{o,y}^{min\text{-}down}}\alpha_{o,y,i,s}^{start}\leq 1,\quad o\in O,y\in Y,t\in T,s\in S. \tag{2.30}$$

We illustrate Equations (2.27) to (2.30) by a small example. Assume we have a converter that must run for at least three periods when started, and must rest for at least two periods when stopped before it can be restarted. Let the converter start up in the beginning of period 1, stop in the end of period 3, then restart in period 6 and stop in period 9. The alpha-variables will be set according to Table 2.2. The converter starts up in the first period (t=1). Equation (2.29) will ensure that $\alpha_t^{end}$ must be 0 for the periods 1 and 2 (since $t+J^{\min-up}-2=1+3-2=2$), and consequently the earliest possible stop is in period 3. If the converter stops in period 3, the earliest possible restart is in period 6. This is ensured by Equation (2.30). Now, t=3 and consequently $\alpha_3^{end}=1$. Then, $\alpha_t^{start}$ must be 0 for t=3, 4 and 5 (since $t+J^{\min-down}=3+2=5$). Equation (2.27) ensures that the output from the converter has a value only if one of the alphas has the value 1. Then the output must be between minimum and maximum power limits. The "min"-formulation is included to handle situations where the converter is started and stopped in the same period. If a converter is running on 1000 kW in a period, and the ramping limits are 400 up and 200 down, Equation (2.28) ensures that the output in the next period must be between 800 and 1400 kW.

*Table 2.2. Example of feasible values for the alpha-variables*

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| $\alpha_t^{start}$ | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| $\alpha_t^{run}$ | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 0 |
| $\alpha_t^{end}$ | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 |

Import $\chi_{a,y,o,t,s}$ of intermittent energy carrier $a \in A^I$ to non-controllable (intermittent) converter unit $o$ must be fixed to the forecasted input. We assume input to be directly in kWh.

$$\chi_{a,o,y,t,s} = I_{o,t,s}, \quad a \in A^I, o \in O, \ t \in T, \ s \in S. \tag{2.31}$$

## Storage unit constraints

For storage unit $l$ we define efficiency factors for charging and discharging, $A_{l,y}^{in}$ and $A_{l,y}^{out}$ respectively. The state of charge, i.e. the storage content, $\sigma_{l,y,t,s}^{soc}$, depends on the state of charge in previous period, $\sigma_{l,y,t-1,s}^{soc}$, charging this period, $\sigma_{l,y,t,s}^{in}$, and discharging $\sigma_{l,y,t,s}^{out}$, in this period.

$$\sigma_{l,y,t,s}^{soc} = \sigma_{l,y,t-1,s}^{soc} + \sigma_{l,y,t,s}^{in} \cdot A_{l,y}^{in} - \frac{\sigma_{l,y,t,s}^{out}}{A_{l,y}^{out}}, \quad l \in L, \ y \in Y, t \in T, s \in S. \tag{2.32}$$

The storage state of charge for storage unit $l$ must be within minimum, $O_{l,y}^{\min}$, and maximum, $O_{l,y}^{\max}$, limits:

$$O_{l,y}^{\min} \le \sigma_{l,y,t,s}^{soc} \le O_{l,y}^{\max}, \quad l \in L, \ y \in Y, t \in T, s \in S. \tag{2.33}$$

Charging, $\sigma_{l,y,t,s}^{in}$, must be below maximum charging capacity, $Q_{l,y}^{in}$, for storage unit *l:*

$$\sigma_{l,y,t,s}^{in} \le Q_{l,y}^{in}, \quad l \in L, y \in Y, t \in T, s \in S. \tag{2.34}$$

Discharging, $\sigma_{l,y,t,s}^{out}$, must be below maximum discharging capacity for storage unit *l*:

$$\sigma_{l,y,t,s}^{out} \le Q_{l,y}^{out}, \quad l \in L, y \in Y, t \in T, s \in S. \tag{2.35}$$

At the end of the planning horizon the storage state of charge, $\sigma^{soc}_{l,y,t,s}$, for storage unit *l* must be above a given limit, $H_{l,y}$:

$$\sigma^{soc}_{l,y,t,s} \geq H_{l,y}, \quad l \in L, y \in Y, t = T, s \in S. \tag{2.36}$$

We illustrate Equations (2.32) to (2.36) by a small example. Assume that we have electric battery storage with maximum 100 kWh storage capacity. We can charge and discharge the battery with 25 kW, and are allowed to fully empty it. The efficiency factor is 0.9 both for charging and discharging. The initial state of charge is 25 kWh, which is also required to be the content in the end of the planning horizon. Table 2.3 illustrates a possible charging and discharging situation. The change in state of charge between periods is controlled by Equation (2.32). Equation (2.33) ensures that the state of charge is between 0 and 100 kWh in every period. Equations (2.34) and (2.35) ensure that charging and discharging is 30 kW or lower. Equation (2.36) forces the final state of charge to be at least 25 kWh.

*Table 2.3. Example of storage decisions*

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| $\sigma_t^{soc}$ (kWh) | 25 | 47,5 | 70 | 97 | 70 | 43 | 16 | 0 | 25 |
| $\sigma_t^{in}$ (kW) | 0 | 25 | 25 | 30 | 0 | 0 | 0 | 0 | 27.8 |
| $\sigma_t^{out}$ (kW) | 0 | 0 | 0 | 0 | 24.3 | 24.3 | 24.3 | 14.4 | 0 |

## Internal energy system balances

In each internal energy system the total energy input and output must balance. The energy inputs are the amounts provided by the converter and the storage units. Outputs are the sum of loads to all load units and charging of storage units.

$$\begin{aligned}\sum_{o \in O} \psi_{o,y,t,s} + \sum_{l \in L} \sigma^{out}_{l,y,t,s} = \sum_{d \in D^I} W_{d,y,t,s} + \sum_{d \in D^S} \omega_{d,y,t,s} + \\ \sum_{d \in D^C} (W_{d,y,t} - \varphi_{d,y,t,s}) + \sum_{l \in L} \sigma^{in}_{l,y,t,s}, y \in Y, t \in T, s \in S.\end{aligned} \tag{2.37}$$

## Non-anticipativity constraints

We have used a variable splitting formulation where a copy of each of the first-stage variables exists for each scenario. Non-anticipativity constraints (Kall & Wallace, 1994) are needed to ensure that these variables take the same value in all scenarios.

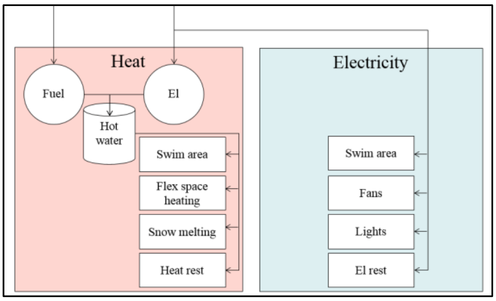
# 2.4. Case study

## Case framework description

We illustrate the properties of the model by a case study based on a Norwegian university college building. The study considers the contract terms for different energy carriers and prices in the Norwegian retail electricity market for 2013. The building contains 30 000 $m^2$ of floor areas, mainly covering auditoriums, offices and common areas as well as a sports area including a swimming pool. Peak energy consumption for the building is approximately 3 000 kWh/h and the yearly total consumption is about 5.3 GWh. During wintertime the main energy load is related to heating, which is delivered through a water-based distribution system and fed from either electric or fuel-fired water heaters. Data and parameters for the building are from the building's owner, Statsbygg, and from studies documented in Grande (2007), Roos (2012) and Twanabasu & Bremdal (2013).

The technology model is split into two internal energy systems, see Figure 2.5: one for electricity specific purposes and one for heat specific purposes. Two external energy carriers feed the energy systems: electricity and fuel. The heat system contains two converter units, one electric water heater and the other fuel-fired water heater. The latter has a startup cost. In order to prevent the fuel-fired water heater from operating on low levels and hence low energy efficiency, the operation staff has decided not to run the electric and fuel-fired water heater simultaneously. However, switching between them is possible at any time. A small hot water storage is modeled and four load units are defined: two shiftable volume types (swimming area and flexible space heating), one shiftable profile (snow melting) and one inflexible covering the remaining load. We have defined six load shift time intervals: One for the swimming area (from hours 1 to 24), four for space heating (hours 9-10, 11-12, 13-14 and 15-16) and one for snow melting (hours 17-24).

The electricity system contains one direct connection converter and four load units: two shiftable volume types (fans in the swimming area and fans in the rooms, each with flexibility according to corresponding units in heat system), one reducible (lights) and also one inflexible.



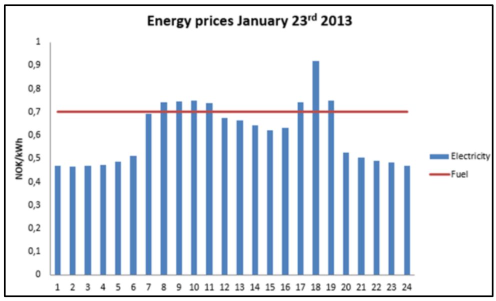




*Figure 2.5. Overview of energy system*

*Figure 2.6. Real energy prices for January 23, 2013*

In the current operation of the building, no flexibility is utilized. The decision to run the el- or fuel-converter is taken once a week, and when started, the converter is running for all hours. For January 2013 the el-converter was running all the time.

In the following, we assume that the building has an electricity supply contract based on Elspot prices on NordPool Spot (Nord Pool, 2015) without mark-up and a grid contract based on terms and prices from the local grid company Fortum Distribution (Fortum Distribution, 2013). The grid contract is a three-part tariff where the peak fee, 57 NOK/kW/month[10], is based on the highest metered hourly load each month.

In order to illustrate how the model works, we have selected to run the case study based on a cold winter day, January 23, 2013. In winter, the high consumption and price variations make the planning problem more challenging than in other seasons. We decide the schedule for the next day in the evening of January 22. At this time NordPool has already published Elspot-prices, so the prices are known with certainty. For the days from January 1 to 22, the registered peak electricity load for the building is 2 821 kWh/h, meaning that the capacity fee for January will as a minimum be based on this value. The energy prices are shown in Figure 2.6, where the electricity price is the sum of the energy fee from the grid contract and the Elspot price. We observe that the fuel price is above the electricity price for all hours except for hours 8, 9, 10, 11, 17, 18 and 19.

We have coded the model outlined in Section 2.3 in FICO Xpress Optimization Suite.

[10] NOK 1 ≈ EUR 0.12

## Deterministic model based on daily load forecasts

We first define our scheduling problem as follows: In the evening on January 22, we decide a schedule for the next day's 24 hours (from h = 1 to 24). Time period h = 1 represents the time interval from 00.00 to 01.00. We make a load forecast according to Appendix 2.B for each of the 24 hours and use the model to optimize the schedule. Since the forecast are expected values, we denote this approach the expected value problem (EV). The schedule consists of decisions for how to utilize the flexible resources, in our case the electric versus the fuel-fired water heater, how to utilize the heat storage and the flexible load units.

Figure 2.7 shows the converter decisions and total amount of electricity and fuel purchased. The green curve is the load forecast. If no flexibility is utilized and the electricity water heater runs, this curve will constitute the planned purchase of electricity. We observe that such a strategy leads to a new peak for the month, approximately 180 kW higher than the previous. To prevent a new peak, we utilize the price variations in electricity during the day and to utilize the price differences between electricity and fuel, the optimization model suggests to run the fuel-fired water heater for four hours from h = 8 to 11. This is done because the electricity price is higher than the fuel price in the whole interval and in order to avoid a new peak in h = 11. The shiftable volume load units are also scheduled to avoid a new peak and to profit from electricity price variations. The snow melting load is delayed for the maximum possible time, since prices are decreasing each hour in the evening. The storage is scheduled to charge from h = 1 to 5, then to discharge from h = 8 to 11. This is followed by a new cycle where the discharging is performed from h = 17 – 19.

This schedule gives a purchase of electricity as illustrated in the red curve in Figure 2.7. Observe that maximum purchase is 2821 kW, which equals the previous monthly maximum. There is no possible cost reduction from reducing the maximum purchase further. We also observe that electricity purchase is substantially reduced in the hours that fuel is cheaper, since the fuel-fired water heater is producing all the heat. Finally, we see that scheduled electricity is higher for h = 1 to 5 and 21 to 24 due to load shifting to cheaper hours.

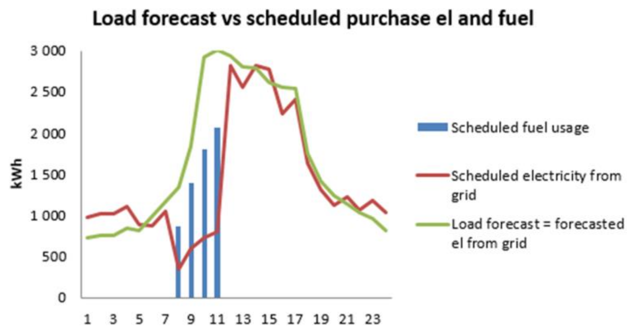



*Figure 2.7. Results from the expected value problem*

Compared to a strategy with no flexibility, we have saved money by avoiding a 182 kW higher peak, representing a monthly cost of NOK 10 374 (cost reduction of 6% on a monthly level) and by reducing the variable cost by NOK 702 (cost reduction of 3% on a daily level).

It should be noted that the peak cost reduction above is constrained by the previous peak. In order to quantify the cost savings potential in real life, the model must be run for a longer horizon. We have run the model for all the days in January and have calculated the net cost savings potential for the whole month to be approximately NOK 75 000. Compared to a strategy where no flexibility is utilized this constitutes 12% of the monthly cost.

## How to handle uncertainty?

The previous section describes an approach where we base our decisions on a load forecast made once a day. The schedule is optimal given that the forecast is right, which in real life is a precondition that normally does not hold. To avoid this problem, we can update the forecast several times during the day, for instance every time we receive updated temperature forecasts, and re-run the scheduling model. We denote this **rolling horizon**.

Because a higher peak cost is the main penalty in our case, we particularly want to capture situations where the outside temperature forecast drops for the high load hours, resulting in a higher load than previously forecasted. Then, to avoid a new peak, we might need to change the schedule, for instance by restarting the fuel-fired water heater in the afternoon.

The upper part of Figure 2.8 illustrates such a situation. Assume that we make an original schedule in the evening and revise it once during the day: at the end of hour 12. This is a simplification to ease the illustration, but the points we want to make are valid even with more frequent updates. First, we schedule for all 24 hours, and implement the decisions for the first 12. Next, at the end of hour 12, we get new information and replan for the last 12 hours. We implement the decisions for these. In the replanning process we may include the 12 first hours for the consecutive day. The upper left curve shows the original load forecast from the evening the day before. The arrow indicates at what time we make the forecast. At the end of hour 12, we have information about the real load for the first 12 hours and updated temperature forecast for the rest of the day. We then update the load forecast for hours 13 – 24. The upper right part of the figure illustrates this situation, presenting real load for the first 12 hours and a hypothetic[11] load forecast for the last 12.

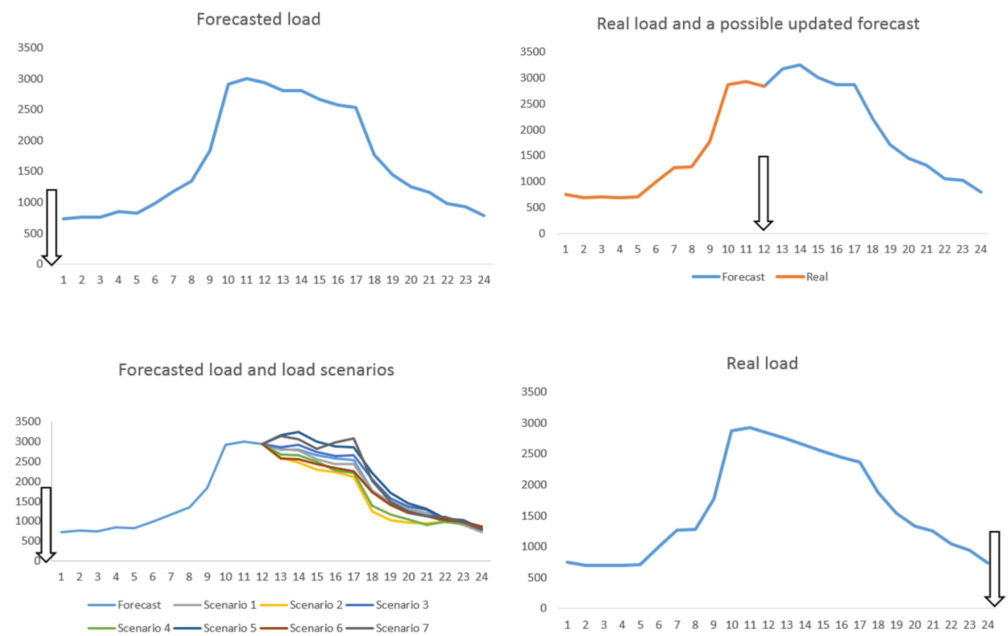



*Figure 2.8. Forecasted load, load scenarios and real load*

At the end of hour 12 we rerun the deterministic model based on the updated load forecast. Contrary to the previous load forecast, the updated one indicates a new peak load in hours 13 – 17. Remember that we originally decided to stop the fuel-fired water heater in hour 11, see the blue bars in Figure 2.7, so currently (in hour 12), it is not in operation. Since we do not have sufficient flexibility in the storage and load units, we need to restart the fuel-fired water

[11] The updated forecast is deliberately picked to illustrate the possible impact from a new afternoon peak

heater to avoid a new peak and added peak cost. However, this strategy gives added cost due to a new startup.

As an alternative to rolling horizon **deterministic** planning, we have rolling horizon **stochastic** planning, where we use the model as described in Section 2.3. This approach also includes an original schedule made the evening before and a revised schedule made at the end of hour 12. Compared to the deterministic, the stochastic explicitly takes into consideration the possibility to get different load realizations for hours 13 – 24 (stage 2). We generate a set of load scenarios according to Appendix 2.C, see the lower left part of Figure 2.8. Each scenario contains a possible load profile over the stage 2 hours. The stochastic model provides first stage decisions for hours 1 – 12 and scenario specific second stage decisions for hours 13 – 24. Similar to the deterministic approach, we just implement the decisions for the hours 1 – 12. The results show that the stochastic solution for the first 12 hours deviate structurally from the deterministic solution by deciding not to stop the fuel-fired water heater at the end of hour 11, but to continue to run also in hour 12. This strategy is more flexible in meeting different realizations of load in the afternoon. When we update the load forecast for hours 13 – 24, we have two options: If the updated forecast indicates a new peak, we continue to run the fuel fired water heater and thus both avoid a new peak and a new startup cost. On the other hand, if the updated forecast does not indicate a new peak, we stop the fuel-fired water heater in hour 12.

This example illustrates that the stochastic model decides a strategy which is more flexible to meet different load realizations. If a high load scenario realizes, the stochastic solution will give reduced costs, since we avoid a new startup. In our example, we have simplified by updating the schedule only once a day. A central question is whether a more frequent (for instance every hour) update of the load forecasts and rerunning the deterministic model could capture the same dynamics. If this rolling deterministic approach does not yield added startups, the stochastic model will not provide added value, and the deterministic approach is sufficiently good. In general, the value of the stochastic model will depend on how much flexibility is available in the building and the magnitude of possible penalization in the case at hand.

However, the scenario tree is still a **model** of load realizations. To compare the deterministic and stochastic approaches properly, we need to look at what happens in real life. The real load will normally not follow any of the scenarios. In our case, the load realized below the forecast for all the hours 13 – 17, see lower right part of Figure 2.8. In retrospect, the decision from the deterministic model (to stop the fuel-fired water heater in hour 11) was the best. According to

Schütz & Tomasgard (2011) we find that for this specific day, the value of stochastic planning (VSP) was 0.

To decide whether a rolling horizon deterministic model is to run hourly or a few times a day would be able to capture enough of the dynamics and flexibility to compete with a stochastic model, a large-scale analysis should be performed over a long time horizon (Maggioni & Wallace, 2010; Schütz & Tomasgard, 2011). We leave this to future research. Such an analysis should also cover other aspects like how often forecasts and schedules should be updated, where to split between stages and consider a multi-stage model. In addition, more advanced forecasting and scenario generation methods and different lengths of the planning horizon should be evaluated.

## 2.5. Conclusion and further work

We propose a new model to support the scheduling process for flexible energy units in buildings. We illustrate the properties of the model in a case study based on a Norwegian university college building. The study shows that the model is able to reduce costs by reducing peak loads and utilizing price differences between periods and between energy carriers. To deal with uncertain parameters, we propose using a rolling horizon approach, where we update the schedules when new temperature forecasts are available. We discuss the properties with deterministic and stochastic models and conclude that the stochastic may be best in cases with limited flexibility in the energy systems in the building and with high penalization for making the wrong decisions. However, in our case the deterministic was sufficiently good. When implementing the model in a real-life setting, a proper long-term analysis should be performed. This is needed to decide the information structure of a stochastic model or alternatively whether a deterministic is sufficient to capture the dynamics and flexibility. The flexibility potential in the internal energy systems, the uncertainty characteristics and the price levels and volatility will also influence the conclusion.

In this paper we have focused on retail side participation in the electricity market. However, if the benefits from Smart Grid technologies are to be realized substantially, the flexibility at demand side should participate in the wholesale side of the market. Further research should focus on optimal bidding strategies for the Day-ahead market and optimal allocation of volumes to different markets and contracts in different time horizons.

## Acknowledgements

We thank Statsbygg for providing data and insightful comments. We also acknowledge support from the Research Council of Norway through the project *Manage Smart in SmartGrids*.

# 2.6. Appendices

## Appendix 2.A. Sets, parameters and variables

### Sets, subsets and indices

| | |
|---|---|
| $T$ | Set of periods, indexed by $t$, |
| $Z \subset T$ | Subset of periods where load curtailment is permitted, |
| $Y$ | Set of internal energy systems, indexed by $y$, |
| $O$ | Set of converter units, indexed by $o$, |
| $O^{2w} \subset O$ | Subset of converter units that can convert in both directions, |
| $A$ | Set of energy carriers, indexed by $a$, |
| $A^{\text{int}} \subset A$ | Subset of energy carriers of type "intermittent", |
| $D$ | Set of load units, indexed by $d$, |
| $D^I \subset D$ | Subset of load units of type "inflexible", |
| $D^S \subset D$ | Subset of load units of type "shiftable", |
| $D^{SV} \subset D$ | Subset of load units of type "shiftable volume", |
| $D^{SP} \subset D$ | Subset of load units of type "shiftable profile", |
| $D^C \subset D$ | Subset of load units of type "curtailable", |
| $D^{CR} \subset D$ | Subset of load units of type "curtailable reducible", |
| $D^{CD} \subset D$ | Subset of load units of type "curtailable disconnectable", |
| $G$ | Set of possible load shift time intervals, indexed by $g$, |
| $G^{SV} \subset G$ | Subset of possible load shift time intervals for shiftable volume load units, |
| $G^{SP} \subset G$ | Subset of possible load shift time intervals for shiftable profile load units, |
| $L$ | Set of storage units, indexed by $l$, |
| $S$ | Set of scenarios, indexed by $s$. |

### Energy carrier parameters

| | |
|---|---|
| $I_{o,t,s}$ | Forecasted supply of intermittent energy carrier to converter $o$ in time period $t$ in scenario $s$ [kWh], |
| $U_a$ | Upper capacity limit for input of energy carrier $a$ [kW], |
| $M_a$ | Highest actual input of energy carrier $a$ given from periods before planning horizon [kW]. |

## Load parameters

| | |
|---|---|
| $W_{d,y,t,s}$ | Load forecast for load unit *d* in system *y* in period *t* in scenario *s* [kWh/period], |
| $T_g^{start}$ | Earliest possible start period for load shift time interval *g*, |
| $T_g^{end}$ | Latest possible end period for load shift time interval *g*, |
| $V_g^{start}$ | Start-period for load forecast for load shift time interval *g*, |
| $V_g^{end}$ | End-period for load forecast for load shift time interval *g*, |
| $B_{d,y}^{\max}$ | Max number of reductions for curtailable load unit *d* in internal energy system *y* during the planning horizon [#], |
| $D_{d,y}^{\max}$ | Maximum duration of a curtailment for curtailable load unit *d* in internal energy system y [# of periods], |
| $D_{d,y}^{\min}$ | Minimum duration between two curtailments for curtailable load unit *d* in internal energy system y [# of periods], |
| $U_{d,y}^{\max}$ | Maximum fraction available for reduction in reducible load unit *d* in internal energy system *y*, |
| $X_{d,y}$ | Disutility cost for curtailed load for load unit *d* in internal energy system *y* [NOK/kWh], |
| $E_{d,y}^{\max}$ | Maximum power for shiftable volume load unit *d* in internal energy system *y* [kW], |
| $E_{d,y,t}^{\min}$ | Minimum power for shiftable volume load unit *d* in internal energy system *y* in time period *t* [kW]. |

## Energy converter parameters

| | |
|---|---|
| $G_{o,y}^{\max}$ | Maximum output from converter unit *o* in internal energy system *y* [kW], |
| $G_{o,y}^{\min}$ | Minimum output (when started) from converter unit *o* in internal energy system *y* [kW], |
| $G_{o,y}^{startup}$ | Startup cost for converter unit *o* in internal energy system *y* [NOK], |
| $A_{o,y}$ | Efficiency parameter for converter unit *o* in internal energy system *y*, |
| $J_{o,y}^{\min-up}$ | Minimum up-time when started for converter unit *o* in internal energy system *y*, |

| | |
|---|---|
| $J_{o,y}^{\min-down}$ | Minimum down-time when stopped for converter unit *o* in internal energy system *y*, |
| $C_{o,y}^{ramp-up}$ | Maximum positive change of output between two periods for converter unit *o* in internal energy system *y*, |
| $C_{o,y}^{ramp-down}$ | Maximum negative change of output between two periods for converter unit *o* in internal energy system *y*. |

## Energy storage parameters

| | |
|---|---|
| $O_{l,y}^{\max}$ | Maximum storage capacity for storage unit *l* in internal energy system *y* [kWh], |
| $Q_{l,y}^{in}$ | Maximum charging capacity for storage unit *l* in internal energy system *y* [kW], |
| $Q_{l,y}^{out}$ | Max discharging capacity for storage unit *l* in internal energy system *y* [kW], |
| $A_{l,y}^{in}$ | Efficiency factor for charging storage unit *l* in internal energy system *y*, |
| $A_{l,y}^{out}$ | Efficiency factor for discharging storage unit *l* in internal energy system *y*, |
| $H_{l,y}$ | Minimum state of charge for storage unit *l* in internal energy system *y* at the end of planning horizon. |

## Prices

| | |
|---|---|
| $P_{a,t,s}^{energy}$ | Energy price for energy carrier of type *a* in period *t* in scenario *s* [NOK/kWh], |
| $P_{a}^{peak}$ | Capacity price for energy carrier *a* [NOK/kW/month], |
| $P_{a,t}^{sales}$ | Sales price for selling back energy carrier *a* in period *t* [NOK/kWh]. |

## Scenarios

| | |
|---|---|
| $R_s$ | Probability that scenario *s* is realized. |

## Variables

| | |
|---|---|
| $\chi_{a,y,o,t,s}$ | Amount of energy carrier *a* imported to converter unit *o* in internal energy system *y* in time period *t* in scenario *s* [kWh], |
| $\chi_{a,t,s}^{import}$ | Net volume imported of energy carrier *a* in time period *t* in scenario *s* [kWh], |
| $\chi_{a,t,s}^{export}$ | Net volume exported of energy carrier *a* in time period *t* in scenario *s* [kWh], |
| $\chi_{a,s}^{peak}$ | Amount that defines the basis for capacity fee of energy carrier *a* in scenario *s* [kW], |
| $\chi_{a,s}^{max}$ | Maximum amount of energy carrier *a* imported in the planning horizon in scenario *s* [kWh], |
| $\psi_{o,y,t,s}$ | Amount of energy produced from converter unit *o* to internal energy system *y* in period *t* in scenario *s* [kWh], |
| $\varphi_{d,y,t,s}$ | Amount of energy reduced from reducible load unit *d* in internal energy system *y* in period *t* in scenario *s* [kWh], |
| $\omega_{d,y,t,s}$ | Delivered energy to shiftable load unit *d* in internal energy system *y* in period *t* in scenario *s* [kWh], |
| $\sigma_{l,y,t,s}^{in}$ | Energy charged to storage unit *l* in internal energy system *y* in period *t* in scenario *s* [kWh], |
| $\sigma_{l,y,t,s}^{out}$ | Energy discharged from storage unit *l* in internal energy system *y* in period *t* in scenario *s* [kWh], |
| $\sigma_{l,y,t,s}^{soc}$ | State of charge for storage unit *l* in internal energy system *y* in period *t* in scenario *s* [kWh], |
| $\delta_{d,y,t,s}^{start}$ | Binary variable = 1 if curtailment of curtailable load unit *d* in internal energy system *y* starts in the beginning of time period *t* in scenario *s*, else 0, |
| $\delta_{d,y,t,s}^{run}$ | Binary variable = 1 if curtailment of load unit *d* in internal energy system *y* is running in time period *t* in scenario *s*, else 0, |
| $\delta_{d,y,t,s}^{end}$ | Binary variable = 1 if curtailment of curtailable load unit *d* in internal energy system *y* ends in the end of time period *t* in scenario *s*, else 0, |
| $\alpha_{o,y,t,s}^{start}$ | Binary variable = 1 if operation of converter unit *o* in internal energy system *y* is starting in the beginning of time period *t* in scenario *s*, else 0, |
| $\alpha_{o,y,t,s}^{run}$ | Binary variable = 1 if operation of converter unit *o* in internal energy system *y* is running in time period *t* in scenario *s*, else 0, |
| $\alpha_{o,y,t,s}^{end}$ | Binary variable = 1 if operation of converter unit *o* in internal energy system *y* stops in the end of time period *t* in scenario *s*, else 0, |
| $\gamma_{g,i,s}$ | Binary variable = 1 if load for load shift interval *g* is moved *i* periods in scenario *s*, else 0. |

## Appendix 2.B. Load forecasting

When we make the schedule, the real load for the building in our case study is unknown, so we need a load forecast. On working days, the load has a clear pattern; a low load level around 500 kW during night hours. In the morning the load increases steeply and in the afternoon it decreases to the low level again, see the green curve in Figure 2.7. For the non-working days the pattern is not so clear, but there is lower load. For load forecasting we use multiple linear regressions with exogenous explanatory variables motivated by Pedersen (2007) and Lindberg & Doorman (2013). The basic assumption in the model is that the total load depends on the hour of the day, whether the hour belongs to a working day or not, the outdoor temperature and finally which month the hour belongs to. In addition, we add a moving average component referring to the residual 24 hours back. We add this MA(24)-component for Tuesdays, Wednesdays, Thursdays and Fridays as long as they are working days. The model is formulated by using binary dummy variables for hours, workdays, non-workdays, months and whether a MA(24)-component is going to be included:

$$\begin{aligned}L_t = \mu &+ \sum_{h=1}^{24} D_{t,h}^{hour} D_t^{workday} \alpha_h^{workday} + \sum_{h=1}^{24} D_{t,h}^{hour} D_t^{workday} \beta_h^{workday} \tau_t + \\ &\sum_{h=1}^{24} D_{t,h}^{hour} D_t^{nonworkday} \alpha_h^{nonworkday} + \sum_{h=1}^{24} D_{t,h}^{hour} D_t^{nonworkday} \beta_h^{nonworkday} \tau_t + \\ &\sum_{m=1}^{12} D_{t,m}^{month} \gamma_m + \sum_{h=1}^{24} D_{t,h}^{hour} D_t^{MA(24)} \theta_h \varepsilon_{t-24} + \varepsilon_t \qquad t \in T\end{aligned} \tag{2.38}$$

Where $t$ is hour number for the year ($t \in \{1...8760\}$) and $h$ is the hour number of the day ($h \in \{1...24\}$). Here $\mu$ is a constant, $\tau_t$ is the outdoor temperature and $\varepsilon_t$ is the residual. We have estimated the parameters by using least squares method and calibrated the model with hourly metered total electricity load for 2012, giving a $R^2 = 0.956$. Table 2.4 gives an overview of parameter values. Descriptive statistics for the residuals are shown in Table 2.5. They have a mean close to 0. Next, we have tested the model on January, February and March 2013. The result is a mean absolute percentage error, MAPE = 10.7%.

*Table 2.4. Overview of the model parameters*

| | |
|---|---|
| $\mu$ | 727 |
| $\gamma^{Jan}$ | 209 |
| $\gamma^{Feb}$ | 205 |
| $\gamma^{Mar}$ | 122 |
| $\gamma^{Apr}$ | 49. |
| $\gamma^{Sep}$ | 42. |
| $\gamma^{Oct}$ | 121 |
| $\gamma^{Nov}$ | 201 |
| $\gamma^{Dec}$ | 211 |

| Ho | $\alpha_h^{workday}$ | $\beta_h^{workday}$ | $\alpha_h^{nonworkday}$ | $\beta_h^{nonworkday}$ | $\theta_h$ |
|---|---|---|---|---|---|
| 1 | -295.8 | -6.6 | -301.1 | -7.7 | -0.269 |
| 2 | -282.4 | -8.1 | -308.2 | -7.4 | -0.329 |
| 3 | -269.6 | -9.8 | -310.2 | -7.2 | -0.431 |
| 4 | -234.4 | -11.6 | -305.0 | -7.7 | -0.062 |
| 5 | -245.3 | -10.4 | -305.3 | -7.3 | -0.106 |
| 6 | -176.1 | -16.6 | -310.8 | -5.3 | -0.209 |
| 7 | -99.1 | -19.6 | -324.5 | -4.4 | -0.358 |
| 8 | 58.2 | -25.5 | -316.2 | -5.1 | -0.211 |
| 9 | 462.8 | -41.0 | -295.2 | -6.9 | -0.578 |
| 10 | 1 126.0 | -64.9 | -274.4 | -7.1 | -0.349 |
| 11 | 1 162.6 | -67.9 | -258.5 | -7.3 | -0.260 |
| 12 | 1 115.6 | -66.8 | -253.2 | -7.4 | -0.219 |
| 13 | 1 053.1 | -65.2 | -258.0 | -6.4 | -0.353 |
| 14 | 1 001.1 | -64.1 | -267.3 | -6.2 | -0.358 |
| 15 | 969.1 | -64.2 | -260.8 | -7.0 | -0.410 |
| 16 | 918.9 | -61.6 | -246.1 | -7.9 | -0.534 |
| 17 | 870.1 | -62.2 | -239.3 | -9.0 | -0.575 |
| 18 | 357.1 | -31.2 | -249.2 | -10.8 | -0.453 |
| 19 | 155.7 | -22.2 | -240.6 | -11.0 | -0.364 |
| 20 | 56.7 | -15.9 | -244.1 | -11.8 | -0.410 |
| 21 | 17.0 | -13.6 | -280.2 | -9.2 | -0.375 |
| 22 | -100.4 | -11.0 | -294.0 | -7.7 | -0.312 |
| 23 | -152.2 | -10.4 | -303.0 | -6.5 | -0.505 |
| 24 | -255.1 | -7.6 | -306.1 | -6.8 | -0.475 |

*Table 2.5. Descriptive statistics for the residuals in the calibration period*

| Mean | Standard deviation | Min | Max |
|---|---|---|---|
| 1.7 | 114.5 | -668.8 | 1 156.5 |

## Appendix 2.C. Scenario generation

To illustrate the properties of the stochastic model. we simplify to a two-stage problem where we split the day into two equal halves. We then assume that the load is known with certainty for stage 1 (h = 1 to 12). For stage 2 (h = 13 to 24) the load is uncertain and will be revealed at the end of period 12 simultaneously for all the hours. See Figure 2.3.

For stage 2 we need to generate load scenarios. We do this by taking the forecasted value for each period and add variation in the scenarios by sampling from the residual time series.

$$L_{h,s} = L_h + \varepsilon_{h,s}, \quad h \in \{13...24\}, s \in S. \tag{2.39}$$

The residuals have a mean close to 0. but they are auto-correlated: a positive residual in one hour yields high probability that the residual is positive also in the following hour. This is useful information for the scenario generation. One possible simple approach would be to sample from the residual series hour by hour and combine randomly into scenarios. Such a method will not take the auto-correlation into account and will yield unrealistically volatile scenarios. Another approach is to split the support of the residuals into intervals (the same for each hour) and find the mean values of these. We then create one scenario per interval, using its mean values for each hour. This will on expectation give 0 mean deviation over all scenarios in each hour. Compared to the first approach these scenarios will be less volatile. However, they will be parallel, and have the same profile as the load forecast. A drawback is that every scenario will have a peak in the same period, which is not realistic. A third alternative is to sample *n* days randomly, and then take the complete residual series from h = 13 to 24 for each sample. This will give realistic scenarios, but the mean of the residuals may deviate from 0. To avoid this, we can repeat the sampling process until we find a sample where the mean is close to 0. Figure 2.9 shows the results from scenario generation methods 2 and 3, each containing seven scenarios.

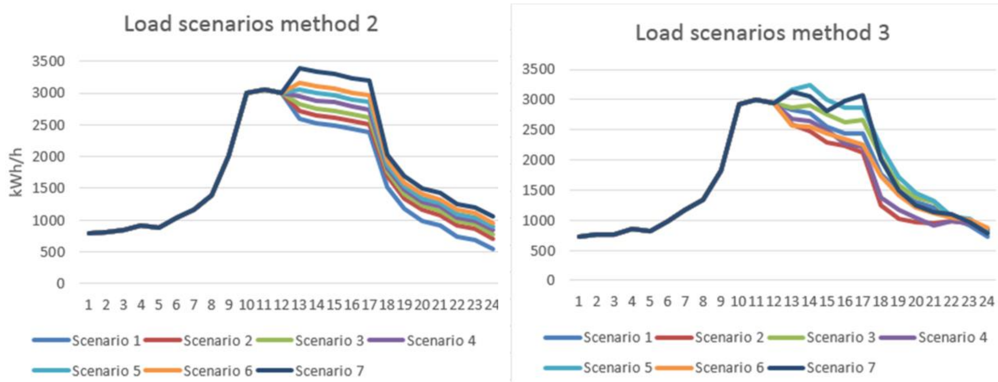



*Figure 2.9. Seven load scenarios generated by methods 2 and 3*

We feel that method 3 provides realistic scenarios with a mean close to 0, capturing auto-correlation and allowing peaks in different periods for different scenarios. An overview of alternative scenario generation methods is given in Kaut & Wallace (2003).

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Paper 2

Stig Ødegaard Ottesen, Asgeir Tomasgard and Stein-Erik Fleten:

# *Prosumer bidding and scheduling in electricity markets*

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# Chapter 3. Prosumer bidding and scheduling in electricity markets

## Abstract

We propose short-term decision-support models for aggregators that sell electricity to prosumers and buy back surplus electricity. The key element is that the aggregator can control flexible energy units at the prosumers. Our objective is total cost minimization by trading in an electricity spot market also taking into consideration costs from grid tariffs, use of fuels and imbalance penalization. We explicitly model the flexibility properties of the underlying energy systems in the prosumers' buildings. In addition, we include the bidding rules and handle the interrelations between hours. Finally, we capture the information structure of uncertain parameters through scenario trees. This results in a two-stage stochastic mixed integer linear program where the bidding decision is made in the first stage and the scheduling in the second. We illustrate the approach in a case study with a diverse portfolio of prosumers. By simulating over a two-month period, we calculate the value of flexibility and the value of stochastic planning.

## 3.1. Introduction

Due to technology developments and policy measures intended to combat climate change, electricity markets all over the world are undergoing dramatic changes (European Commision, 2015). One change driver is the integration of non-dispatchable renewable electricity generation from solar photovoltaic and wind power systems. New types of electricity loads for electric vehicles and heating are other such drivers. Some of the consequences are that there is less predictability and faster changes in the generation and loads. Since these changes are taking place in the distribution grid, demand side flexibility is a key resource in order to balance supply and demand, so as to be able to operate the electricity grid within safe limits and to avoid massive investments (GEODE, 2014). According to ENTSO-E (2014), the demand side should participate as much as possible in all markets and contribute to overcome system scarcities.

Applicable decision-support models are needed to let the demand side participate actively in the electricity markets and reduce problems with market failure. In Ottesen & Tomasgard (2015) we developed a modelling concept for a single building participating in the end-user market. We split the demand side units according to their flexibility properties: Inflexible loads, shiftable and curtailable loads, dispatchable converters/generators and energy storages. In order to handle multiple energy carriers, we based our approach on the energy hub concept (Geidl & Andersson, 2007).

In this paper, we extend our scope to cover several buildings participating in the wholesale electricity market. We are inspired by the concept of aggregation of smaller consumers (Eurelectric, 2014), but our work is also relevant for single larger consumers. Since we want to cover local generation, we use the term prosumer, defined as a consumer who produces electricity (European Commision, 2015).

Many articles focus on optimal integration of local generation, storage and flexible loads in the context of a microgrid or virtual power plant, see for instance Faria et al. (2014), Heydarian-Forushani et al. (2014), López et al. (2015), Mazidi et al. (2014), Roos, Ottesen, & Bolkesjø (2014), Shayeghi & Sobhani (2014), Shi, Luo, & Tu (2014), Zakariazadeh, Jadid, & Siano (2015) and Zapata, Vandewalle, & D'haeseleer (2014). We contribute by taking the bidding process and market rules explicitly into account and model the information revelation process for the uncertain parameters.

A comprehensive list of reference work is available regarding generation scheduling, see for instance Li, Shi, & Qu (2011). However, much of the work focuses only on the scheduling part, without taking the bidding process into consideration. De Ladurantaye, Gendreau, & Potvin (2007) empirically demonstrate that models that integrate the bidding process outperform those where the bidding process is disregarded.

Fleten & Kristoffersen (2007) determine optimal bidding strategies for a hydropower producer with two power stations in series and with one storage (reservoir) for each station. They assume uncertain market prices and model the decision process as a two-stage stochastic program. Here the bidding decision belongs to stage one, while the scheduling decision belongs to stage two, when prices are revealed. They define bidding constraints for piecewise linear hourly bids and for block-bids valid for a number of consecutive hours. In addition, they define the technical constraints for the power stations, the reservoirs and the watercourses. Due to the start-up costs for the power stations, the decision problem becomes a mixed integer linear stochastic program.

Aasgård et al. (2014) take this one step further as they also take uncertain inflow into account as well as the fact that in real life the data realizations will not follow any of the predefined scenarios. They also compare a deterministic approach with a stochastic one and report that the mean price earned per produced MWh is higher by explicitly modelling uncertainty.

In current electricity markets, a normal bidding procedure for retailers and large consumers is to bid the expected load independent of the price. There are different reasons for this “flat bid” strategy: small end-users are currently not exposed to time-varying prices, the technical infrastructure for direct control of load is not in place and the price variations during the day and the imbalance penalties are small. We expect this to change in the near future, which increases the value of more advanced bidding procedures.

Compared to the literature covering production side bidding and scheduling, there is little literature focusing on demand side bidding. Among the few publications, the work often simplifies the problem by disregarding the bidding process and only considers the decision for a single hour or avoids the proper representation of the physical properties of the underlying energy system.

The work presented in Fleten & Pettersen (2005) covers the bidding process for a retailer in the Norwegian electricity market. A piecewise linear bid curve is constructed for a single hour, taking into consideration uncertain prices and potential penalization from the imbalance market. The load is represented as an inverse demand-function.

In the work by Zare, Moghaddam, & Sheikh El Eslami (2010) optimal bid curve construction is presented for a large consumer with the possibility for self-generation. They assume uncertain and normally distributed market prices and no auto correlation. No interrelation between hours is treated.

Garnier & Madlener (2014b) explore the economic benefits that wind and photovoltaic power plant operators can extract from demand-side flexibility. They compare two alternatives: 1) To maximize relative day-ahead market value in view of price developments and 2) intraday operations to minimize costs incurred when balancing forecast errors. Furthermore, in Garnier & Madlener (2014a) they optimize volume and timing decisions in the intraday market to balance forecast errors.

In this paper we use the scheduling model outlined in Ottesen & Tomasgard (2015) as our starting point regarding energy systems in buildings with special focus on flexibility properties. Next, we use the concepts from Fleten & Kristoffersen (2007) and Aasgård et al. (2014) to handle the bidding process. However, we use this for a different type of market participant, an aggregator representing a portfolio of prosumers. The aggregator delivers electricity to the prosumers, receives surplus electricity and trades the net demand in a wholesale market, which we denote the electricity spot market. Imbalances between commitments in the spot market and real purchase/sales are settled according to prices and rules from a balancing market. Depending on the regulation in each country, the prosumers may have entered a grid contract with the local grid company. Finally, the prosumers with thermal generators or converters buy fuel from a fuel provider.

We assume that the aggregator's task is to minimize the costs for the prosumers in total. We leave to further research how the benefits should be distributed between the aggregator and each of the prosumers. Furthermore, we assume that the aggregator is risk neutral and is a price-taker. Risk averse aggregators can still use this approach. Risk can be mitigated by hedging and insurance programs. Reducing risk through changing operating decisions can be costly compared to financial operations (Fleten, Wallace, & Ziemba, 2002).

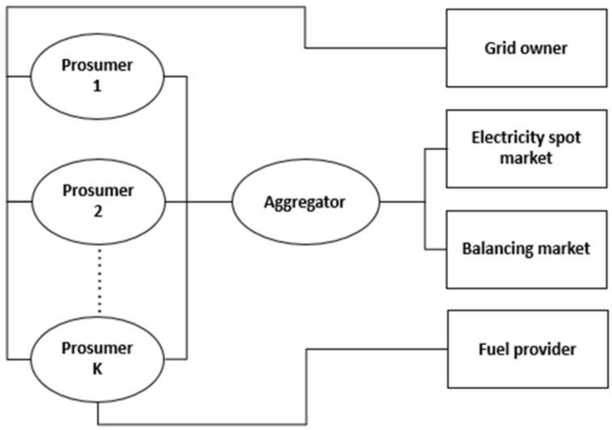


*Figure 3.1. Overview of the involved entities*

Since we expect market design changes in the future, we keep the model as general as possible. Such changes can be market clearing closer to operation, shorter than one day trading horizons or shorter than one hour trading periods (Barquin, Rouco, & Rivero, 2011).

The main contribution from this article is the representation of the bidding process seen from demand side taking into consideration the interrelation between hours and the connection to the underlying physical energy system in the portfolio of prosumers. We model the bidding and scheduling process as a two-stage stochastic program, where uncertain parameters are represented in scenario trees. We illustrate this by including a case study where we also calculate the value of flexibility and the value of stochastic planning for a specific Norwegian case simulated over a two-month period.

The remainder of the paper is organized as follows: Section 3.2 outlines the bidding and scheduling process. The mathematical formulations are presented in Section 3.3, while Section 3.4 contains the case study.

## 3.2. The bidding and scheduling process

The aggregator has two decisions to make: First, before market gate closure, he needs to decide the optimal bid to send to the spot market for all periods within the trading horizon. Secondly, he needs to decide the optimal schedules for every flexible unit in the portfolio. Figure 3.2 describes this process.

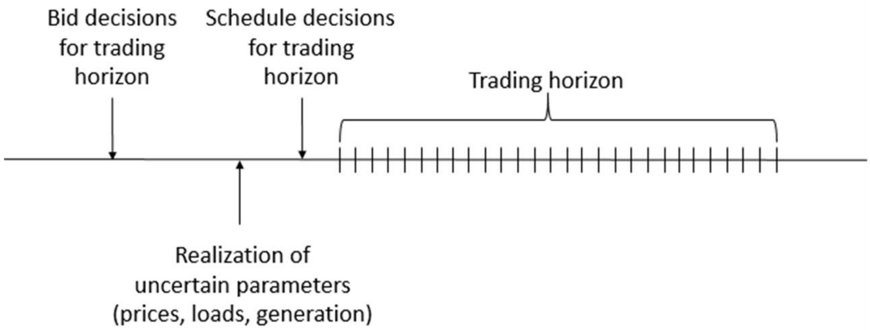


*Figure 3.2. Illustration of the information and decision process*

The bid decision must be made under uncertainty, since we do not know what values the prices, loads and generation will have for the periods in the trading horizon. We model the uncertainty explicitly in a two-stage stochastic recourse program (Kall & Wallace, 1994). The uncertain parameters are represented by discrete probability distributions in a two-stage scenario tree, as illustrated in Figure 3.3. Each path through the tree from the root node (to the left) to one of the leaf nodes (to the right) is called a scenario and represents a possible realization of all the uncertain parameters, see the right hand side of Figure 3.7 and Appendix 3.B for examples of scenarios. We assign a probability to each scenario. For more information about scenarios and scenario generation methods, see for instance Kall & Wallace (1994) or Kaut & Wallace (2003). When making the bid decisions (stage one decisions), we take into account the different possible outcomes of the uncertain parameters in the operations phase (stage two). Because the two stages are optimized simultaneously, the bid decisions are made recognizing the expected cost of the operational scenarios.

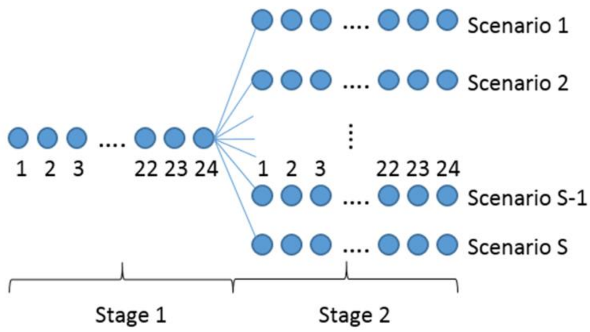


*Figure 3.3. Two-stage scenario tree*

After the market clearing process, the market operator publishes the realized market prices and the aggregator's market commitments.

The aggregator's next decision is the optimal schedules for every flexible unit. As a simplification, we assume that we know both the loads and generation with certainty in this stage. Hence, the scheduling problem is deterministic. The optimal schedules give minimum costs, where the cost elements are the same as for the bidding problem, except for the spot costs, since these are given from the market commitments. Note that both the bid and the schedules are for all periods within the trading horizon.

We keep our model general in terms of the time for gate closure, length of trading horizon and granularity of trading periods. However, to explain the concept, we look to current market design and rules in the Norwegian electricity wholesale market (Nord Pool Spot, 2014). Note that similar rules exist in electricity markets in different countries. In the Elspot Day-ahead-market, operated by Nord Pool Spot, the gate closure is at 12:00 CET every day. Before this deadline, every market participant must submit sales or purchase bids for the coming 24 hours starting from 00:00 CET. The participants are required to make their bids so they can fulfill the resulting commitment. We call this to plan into balance. Next, between 12:30 and 12:45, Nord Pool Spot publishes market prices for each hour, and the market commitments are given. Then the participants decide the physical schedules at the unit level. Since bidding to the Elspot market is done 12 – 36 hours before the operation phase, imbalances may occur, for instance due to changed weather conditions. Such imbalances are penalized in the balancing market. Trading in the intraday market, Elbas (also operated by Nord Pool Spot), may be used to adjust the market commitments and hence avoid imbalance costs. During the operation hour (real time), the transmission system operator (TSO), Statnett in this example, uses several short-term balancing and reserve markets to secure safe operation of the electricity system. The imbalance market prices are decided based on real-time actions, and will not be set before each hour is passed. Then each participant's imbalances are calculated and financially settled according to balancing market rules.

In normal situations, the Norwegian imbalance prices rarely deviate more than 30 % from the Elspot price. In more extreme situations, however, the market participants have experienced imbalance prices up to 5 times the Elspot prices. With more intermittent and unpredictable renewable generation and more dynamics at the demand side, we expect imbalance prices to deviate more from Elspot prices in the future.

The main objective in this paper is to develop a bidding and scheduling model that plans for balance. We simplify the problem by not considering intraday trading. This decision can be justified since intraday trading may involve costly and time-consuming tasks, such as replanning and communicating these revised plans to the market operator and involved departments. Furthermore, we do not model the balancing market in detail, rather as a penalization of the imbalance volume. The penalty represents the difference between the prices in the Elspot market and the balancing market. We leave a more detailed modelling of the intraday and balancing markets to further research.

In the Elspot market, Nord Pool Spot announces a price range defined by a lower and an upper bid price limit. All bid prices must be within these limits. Currently (effective from 1 July 2014) the price range is from -500 €/MWh to +3 000 €/MWh. The market participants can choose between three different bid types: Hourly bids, flexible hourly bids and block bids. For other European electricity markets, other bid types also exist (PCR PXs, 2013). However, hourly bids are the most common type. In our mathematical formulation we include hourly bids and block bids.

In each **hourly bid** the participant submits a set of bid prices and energy volumes for each hour. The first and last price-point must be the lower and the upper price limit, respectively. Up to 62 price-points may be freely chosen between the limits, with 0.1 €/MWh as the smallest possible step. Nord Pool Spot then interprets the bid as a piecewise linear function between the points, see Figure 3.4. The energy volume given in an hourly bid for purchase must be constant or decreasing with increasing bid prices.

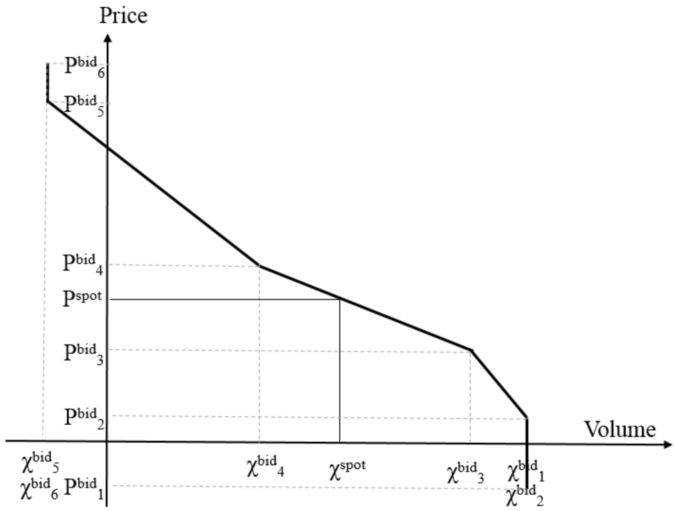


*Figure 3.4. Illustration of hourly bid curve for one hour*

A **block bid** is a participant's willingness to purchase or sell a specified energy volume at a specified bid price during a minimum of three consecutive hours. A block bid must be accepted as a whole or not accepted at all. The participant specifies the bid price, the hourly energy volume per block and the start and stop times.

Since we want to keep generality and open for other time resolutions than hourly, we denote the hourly bid-format "single period bid".

As pointed out earlier, the examples above are taken from the Norwegian electricity markets, but our proposed model is designed to handle different market rules and conditions.

# 3.3. The scheduling problem and the mathematical formulation

In this section, we outline the mathematical formulation for the bidding and scheduling problem. We describe the sets, parameters and variables successively as they appear. A full list is found in Appendix 3.A.

## Objective function for the bidding problem

The objective is to minimize the expected total cost over the planning horizon:

$$\min z = \sum_{s \in S} R_s \left[ \sum_{t \in T} \begin{pmatrix} P_{t,s}^{spot} \chi_{t,s}^{spot} + P_{t,s}^{grid-import} \chi_{t,s}^{total-import} + P_{t,s}^{grid-export} \chi_{t,s}^{total-export} \\ +P_t^{imbal} \mid \chi_{t,s}^{imbal} \mid + \kappa_{t,s}^{startup} + \kappa_{t,s}^{fuel} + \kappa_{t,s}^{curtail} \end{pmatrix} \right], \tag{3.1}$$

where $R_s$ is the probability of scenario s. The first element in the objective function represents costs from spot-purchase, where we multiply the spot-price, $P_{t,s}^{spot}$, with the volume purchased or sold, $\chi_{t,s}^{spot}$, in period *t* and scenario *s*. A negative value of $\chi_{t,s}^{spot}$ represents sales. Since we assume a pay-as-cleared principle at the spot market, the price will be the same for both purchase and sales. The volume purchased or sold consists of commitments from single period bids, $\chi_{t,s}^{com}$, and block bids, $\overline{\chi}_{t,s}^{com}$:

$$\chi_{t,s}^{spot} = \chi_{t,s}^{com} + \overline{\chi}_{t,s}^{com}, \quad t \in T, s \in S, \tag{3.2}$$

where $\overline{\chi}_{t,s}^{com}$ represents the contribution from block bid commitments to the actual period $t$.

The second and third elements cover costs to the grid owner, representing the grid cost from importing (taking out) from and exporting to (feeding into) the grid, respectively. We assume different prices for import $P_{t,s}^{grid-import}$ and export $P_{t,s}^{grid-export}$.

We calculate the total amount of electricity imported from or exported to the grid by:

$$\chi_{t,s}^{total-import} = \max((\sum_{k \in K} \chi_{k,a,t,s}), 0), \quad a = 1, t \in T, s \in S \tag{3.3}$$

$$\chi_{t,s}^{total-export} = -\min((\sum_{k \in K} \chi_{k,a,t,s}), 0), \quad a = 1, t \in T, s \in S \tag{3.4}$$

where $\chi_{k,a,t,s}$ is the amount of energy carrier *a* imported to prosumer *k* in period *t* and scenario *s*. Electricity corresponds to energy carrier *a=1*. Note that a prosumer may be a single prosumer or a group of prosumers, depending on the case at hand.

The imbalance penalty price, $P_t^{imbal}$, multiplied with the absolute value of imbalance volume $|\chi_{t,s}^{imbal}|$ represents penalty costs from commitment deviations. Note that we in this paper have decided to handle the imbalance with a predefined penalty price. If we, otherwise, had decided to handle it according to an uncertain imbalance market price, it would be scenario dependent, and hence have a scenario index: $P_{t,s}^{imbal}$.

The imbalance volume is the deviation between the spot market commitment and the real exchange.

$$\chi_{t,s}^{imbal} = \chi_{t,s}^{spot} - \sum_{k\in K} \chi_{k,a,t,s}, \quad a=1,\ t\in T, s\in S \tag{3.5}$$

The three last elements in the objective function relate to activities in the internal energy system of each prosumer.

First, we have the costs for starting up converter units $\kappa_{t,s}^{startup}$ defined by multiplying the start-up price $P_o^{startup}$ for each converter *o* with the binary variable $\alpha_{o,t,s}^{start}$ which is set to 1 in the period if and only if the converter is started up.

$$\kappa_{t,s}^{startup} = \sum_{o\in O} P_o^{startup} \alpha_{o,t,s}^{start}, \quad t\in T, s\in S \tag{3.6}$$

We calculate the total fuel costs $\kappa_{t,s}^{fuel}$ as the product of the fuel price $P_a^{fuel}$ and the total amount of fuel $\chi_{a,t,s}^{fuel}$ of energy carrier type *a* summed over all energy carrier types except for electricity. Other operational costs may also be included here:

$$\kappa_{t,s}^{fuel} = \sum_{a\in A\backslash 1} \sum_{o\in O} P_a^{fuel} \chi_{a,o,t,s}, \quad t\in T, s\in S \tag{3.7}$$

Finally, we have costs for curtailing loads, $\kappa_{t,s}^{curtail}$, which are found by multiplying the price of curtailment, $P_d^{curtail}$, with the volume curtailed, $\varphi_{d,t,s}$, summed over all curtailable load units.

$$\kappa_{t,s}^{curtail} = \sum_{d \in D^c} P_d^{curtail} \varphi_{d,t,s}, \quad t \in T, s \in S \tag{3.8}$$

# Bidding constraints

## Single period bids

A single period bid is defined by a set of bid points consisting of a bid price and a bid volume. Since selecting both values of bid prices and bid volumes is a nonlinear problem, we approximate by fixing the price points $P_i^{bid}$ exogenously (similar to Aasgård et al. (2014)). Then our problem is to decide the bid volumes $\chi_i^{bid}$.

From Figure 3.4 we see that the committed volume $\chi^{com}$ can be calculated by:

$$\chi^{com} = \chi_4^{bid} + \frac{\chi_3^{bid} - \chi_4^{bid}}{P_4^{bid} - P_3^{bid}} (P_4^{bid} - P^{spot}), \tag{3.9}$$

where $P^{spot}$ is the market clearing price. We omit the period index for ease of exposition. In general, we can formulate the relation as:

$$\chi^{com} = \frac{P^{spot} - P_{i-1}^{bid}}{P_i^{bid} - P_{i-1}^{bid}} \chi_i^{bid} + \frac{P_i^{bid} - P^{spot}}{P_i^{bid} - P_{i-1}^{bid}} \chi_{i-1}^{bid}, \qquad if \; P_{i-1}^{bid} < P^{spot} \le P_i^{bid} \tag{3.10}$$

where $i \in I$ is the bid-point.

Extending to a scenario formulation and including periods we get:

$$\chi_{t,s}^{com} = \frac{P_{t,s}^{spot} - P_{i-1}^{bid}}{P_i^{bid} - P_{i-1}^{bid}} \chi_{i,t}^{bid} + \frac{P_i^{bid} - P_{t,s}^{spot}}{P_i^{bid} - P_{i-1}^{bid}} \chi_{i-1,t}^{bid}, \; P_{i-1}^{bid} < P_{t,s}^{spot} \le P_i^{bid}, \; i \in I, \; i \ne 1, \; t \in T, s \in S \tag{3.11}$$

According to the bidding rules, the volume points must be non-increasing with increasing price:

$$\chi_{i,t}^{bid} \le \chi_{i-1,t}^{bid}, \quad i \in I, \; i \ne 1, \; t \in T \tag{3.12}$$

## Block bids

A block bid is valid for a block *b* defined by its start period $T_b^{start}$ and end period $T_b^{end}$. For each block it is possible to bid a volume $\overline{\chi}_{i,b}^{bid}$ for each of the predefined bid prices $P_i^{bid}$ which are the same as for the single period bids. The total bid for one price is the sum of all volumes bid to lower prices. There is no constraint for the block bid volumes.

For each price point, a volume $\overline{\chi}_{i,b}^{bid}$ must be decided for the block bid. The block bid for purchase is accepted if the average spot price is equal to or lower than the bid price. The total committed purchased volume for a block is the sum of the volumes for all prices that are equal to or lower than the average spot price. For sales, we will have the opposite situation:

$$\overline{\chi}_{b}^{com} = \sum_{i \in I | P_i \geq P_{b,s}^{ave}} \overline{\chi}_{b,i}^{bid}, \quad b \in B, \ \overline{\chi}_{b,i}^{bid} > 0, \ s \in S \tag{3.13}$$

$$\overline{\chi}_{b}^{com} = \sum_{i \in I | P_i \leq P_{b,s}^{ave}} \overline{\chi}_{b,i}^{bid}, \quad b \in B, \ \overline{\chi}_{b,i}^{bid} < 0, \ s \in S \tag{3.14}$$

For each period the contribution from block bid commitments is:

$$\overline{\chi}_{t,s}^{com} = \sum_{b \in B | T_b^{start} \leq t \leq T_b^{end}} \overline{\chi}_{b,s}^{com}, \quad t \in T, \ s \in S \tag{3.15}$$

## Shiftable load unit constraints

For **Shiftable load units** the total load must always be met, but it may be moved within a given time interval. We distinguish between **Shiftable volume load units** (where the total volume must be met over a set of time periods, but the profile can change within limits) and **Shiftable profile load units** (that can be moved, but where the energy profile cannot be changed).

For shiftable volume load units $d \in D^{SV}(k, y)$ we define load shift time intervals $g \in G(d)$ with a start period $T_g^{start}$ and an end period $T_g^{end}$.

For each load shift interval, the planned sum of energy amount $\omega_{d,t,s}$ delivered to shiftable volume load unit *d* over the interval must equal the sum of load forecast $W_{d,t,s}$:

$$\sum_{t=T_g^{start}}^{T_g^{end}} \omega_{d,t,s} = \sum_{t=T_g^{start}}^{T_g^{end}} W_{d,t,s},\ d \in D^{SV}(k,y), g \in G(d),\ s \in S. \tag{3.16}$$

The energy amount $\omega_{d,t,s}$ delivered to the shiftable volume load unit *d* must be between the minimum $E_d^{min}$ and maximum constraint, $E_d^{max}$:

$$E_d^{min} \le \omega_{d,t,s} \le E_d^{max}, \qquad t \in T^g,\ d \in D^{SV}(k,y),\ g \in G(d),\ s \in S. \tag{3.17}$$

For shiftable profile load units, we introduce the binary decision variable $\gamma_{g,n,s}$ which is set to 1 if the load is shifted *n* periods. Exactly one shifting option must be selected for each shiftable profile load unit in load shift time interval *g*:

$$\sum_{n=T_g^{start}-V_g^{start}}^{T_g^{end}-V_g^{end}} \gamma_{g,n,s} = 1, \qquad g \in G(k,d,y),\ s \in S. \tag{3.18}$$

Here, $T_g^{start}$ and $T_g^{end}$ are the earliest start and the latest end, respectively, for the load shift interval, while $V_g^{start}$ and $V_g^{end}$ are the first and last period for the load forecast. The delivered energy $\omega_{d,t,s}$ to load unit *d* in time period *t* in scenario *s* is then determined by:

$$\begin{aligned} \omega_{d,t,s} &= \sum_{n=0}^{T_g^{end}-T_g^{start}} \gamma_{g,(t-T^{start}-n),s} W_{d,(T^{start}+n),d}, \\ t &\in \left\{T_g^{start}, T_g^{end}\right\}, d \in D(k,y), g \in G(k,d,y), s \in S \end{aligned} \tag{3.19}$$

For more details about shiftable load units, see Ottesen &Tomasgard (2015).

## Curtailable load unit constraints

We introduce binary variables to control the curtailments. First, $\delta_{d,t,s}^{start}$ gets the value 1 in periods where curtailment is started up in the beginning of the period. Next, $\delta_{d,t,s}^{end}$ gets the value 1 in periods where curtailment is stopped at the end of the period. Finally, $\delta_{d,t,s}^{run}$ gets the value 1 in periods where curtailment is ongoing, but not started or stopped in the same period.

For the load units that can be curtailed, we limit the duration to $D_{d,y}^{max}$ periods:

$$\sum_{i=t}^{t+D_{d,y}^{max}-1} \delta_{d,y,i,s}^{end} \geq \delta_{d,y,t,s}^{start}, \quad d \in D^C(k,y), s \in S. \tag{3.20}$$

The number of load curtailments must be constrained by the maximum allowable number of curtailments $B_d^{max}$:

$$\sum_{t \in Z} \delta_{d,t,s}^{start} \leq B_d^{max}, d \in D^C(k,y), s \in S. \tag{3.21}$$

A minimum duration $D_d^{min}$ must exist between two load curtailments:

$$\delta_{d,t}^{end} + \sum_{i=t}^{t+D_d^{min}} \delta_{d,i}^{start} \leq 1, \quad d \in D^C(k,y), t \in Z. \tag{3.22}$$

The reduced volume $\varphi_{d,t,s}$ can only have a non-zero value in periods where reduction starts, is running or ends. The reduced volume must be constrained by the maximum reducible fraction $U_d^{max}$ times the forecast $W_{d,t,s}$:

$$\varphi_{d,t,s} \leq U_d^{max} W_{d,t,s} \min((\delta_{d,t,s}^{start} + \delta_{d,t,s}^{run} + \delta_{d,t,s}^{end}),1), \ \ d \in D^{CR}(k,y), t \in Z, s \in S. \tag{3.23}$$

Disconnectable load units can only be on or off, hence the reduced volume must be either 0 or equal to the total forecast $W_{d,t,s}$:

$$\varphi_{d,t,s} = W_{d,t,s} \cdot \min((\delta_{d,t,s}^{start} + \delta_{d,t,s}^{run} + \delta_{d,t,s}^{end}),1), \quad d \in D^{CD}(k,y), t \in Z, s \in S. \tag{3.24}$$

## Converter unit constraints

Similar to curtailable load units, we introduce binary variables, $\alpha_{o,t,s}^{start}, \alpha_{o,t,s}^{run}, \alpha_{o,t,s}^{end}$ and constraints to control the start-up, the operation and the shut-down of converter units.

In periods where the converter is in operation, the amount of energy output $\psi_{o,t,s}$ must be between minimum $G_o^{min}$ and maximum $G_o^{max}$ output, else 0:

$$\min((\alpha_{o,t,s}^{start} + \alpha_{o,t,s}^{run} + \alpha_{o,t,s}^{end}),1)G_o^{max} \geq \psi_{o,t,s} \geq \min((\alpha_{o,t,s}^{start} + \alpha_{o,t,s}^{run} + \alpha_{o,t,s}^{end}),1)G_o^{min}, \quad o \in O(k,y), t \in T, s \in S. \tag{3.25}$$

Between two consecutive periods, the change of energy output, $\psi_{o,t,s}$, for converter unit *o* must be between ramping limits $C_o^{ramp-up}$ and $C_o^{ramp-down}$:

$$\psi_{o,t-1,s} + C_o^{ramp-up} \geq \psi_{o,t,s} \geq \psi_{o,t-1,s} - C_o^{ramp-down}, \quad o \in O(k,y), t \in T, s \in S. \tag{3.26}$$

When started, there must be a minimum running time $J_o^{min\text{-}up}$ for converter unit *o*:

$$\alpha_{o,t,s}^{start} + \sum_{n=t}^{t+J_o^{min-up}-2} \alpha_{o,n,s}^{end} \leq 1, \quad o \in O(k,y), t \in T, s \in S. \tag{3.27}$$

Similarly, a minimum duration $J_o^{min-down}$ must exist between two operations:

$$\alpha_{o,t,s}^{end} + \sum_{n=t}^{t+J_o^{min-down}} \alpha_{o,n,s}^{start} \leq 1, \quad o \in O(k,y),\ t \in T, s \in S. \tag{3.28}$$

For energy converter unit *o* we define the relation between input $\chi_{a,o,t,s}$ and output $\psi_{o,t,s}$ in the following way:

$$\psi_{o,t,s} = A_o \cdot \chi_{a,o,t,s}, \quad o \in O(k,y), t \in T, s \in S, \tag{3.29}$$

where $A_o$ is the efficiency function for the converter unit.

The import $\chi_{a,o,t,s}$ of intermittent energy carrier $a \in A^I$ to the non-controllable (intermittent) converter unit *o* must be fixed to the forecasted input. We assume input to be directly in kWh.

$$\chi_{a,o,t,s} = I_{o,t,s}, \quad a \in A^I,\ o \in O(k,y),\ t \in T,\ s \in S. \tag{3.30}$$

## Storage unit constraints

For storage unit $l$ we define efficiency factors for charging and discharging, $A_l^{in}$ and $A_l^{out}$, respectively. The state of charge, i.e. the storage content, $\sigma_{l,t,s}^{soc}$, is dependent on the state of charge in previous period $\sigma_{l,t-1,s}^{soc}$, charging in current period $\sigma_{l,t,s}^{in}$ and discharging $\sigma_{l,t,s}^{out}$ in current period.

$$\sigma_{l,t,s}^{soc} = \sigma_{l,t-1,s}^{soc} + \sigma_{l,t,s}^{in} \cdot A_l^{in} - \frac{\sigma_{l,t,s}^{out}}{A_l^{out}}, \quad l \in L(k,y), t \in T, s \in S. \tag{3.31}$$

The storage state of charge for storage unit $l$ must be within minimum, $O_l^{min}$, and maximum, $O_l^{max}$, limits:

$$O_l^{min} \le \sigma_{l,t,s}^{soc} \le O_l^{max}, \quad l \in L(k,y), t \in T, s \in S. \tag{3.32}$$

Charging $\sigma_{l,t,s}^{in}$ must be below the maximum charging capacity $Q_l^{in}$ for storage unit *l:*

$$\sigma_{l,t,s}^{in} \le Q_l^{in}, \quad l \in L(k,y),\ t \in T, s \in S. \tag{3.33}$$

Discharging $\sigma_{l,t,s}^{out}$ must be below the maximum discharging capacity for storage unit *l*:

$$\sigma_{l,t,s}^{out} \le Q_l^{out}, \qquad l \in L(k,y),\ t \in T, s \in S. \tag{3.34}$$

## Internal energy system balances

The total energy input and output must balance for each prosumer and internal energy system. The energy inputs are the amounts provided by the converter and the storage units. Outputs are the sum of loads to all load units and charging of storage units.

$$\sum_{o\in O(k,y)} \psi_{o,t,s} + \sum_{l\in L(k,y)} \sigma_{l,t,s}^{out} = \sum_{d\in D^I(k,y)} W_{d,t,s} + \sum_{d\in D^S(k,y)} \omega_{d,t,s}$$
$$+ \sum_{d\in D^C(k,y)} (W_{d,t} - \varphi_{d,t,s}) + \sum_{l\in L(k,y)} \sigma_{l,t,s}^{in},\ k\in K, y\in Y, t\in T, s\in S. \tag{3.35}$$

## Objective function and constraints for the scheduling problem

The objective function for the scheduling problem contains the same elements as for the bidding problem, except the spot costs which were decided in the bidding problem:

$$\min z = \sum_{t\in T}\begin{pmatrix} P_t^{grid-import}\chi_t^{total-import} + P_t^{grid-export}\chi_t^{total-export} \\ +P_t^{imbal} \mid \chi_t^{imbal} \mid +\kappa_t^{startup} + \kappa_t^{fuel} + \kappa_t^{curtail} \end{pmatrix} \tag{3.36}$$

Since all parameters now are known with certainty, the scheduling problem is deterministic, and we will have no scenarios and hence no scenario indices in the objective function or in the constraints. Equations (3.16) to (3.35), without scenario indices, are also valid for the scheduling problem. Remember that this is a simplification. In real life, generation from sun and wind and load will still be uncertain.

# 3.4. Case study

## Portfolio description

We create a test case with an aggregator that controls flexible energy units for prosumers in the Norwegian electricity market. We assume an illustrative portfolio of two prosumers: 1) a community consisting of public/commercial buildings, households and summer cottages and 2) an industrial plant in the process industry.

We base the community prosumer on information from the municipality of Hvaler, south-east in Norway. Hvaler has 6 800 electricity consumers, where approximately 4 300 are summer cottages, 2 400 are households and the rest is a mix of public, commercial and service buildings and small industries. We represent the community as one aggregated prosumer. In 2011, the grid company installed smart metering equipment at every consumer, meaning that hourly meter values are available. In addition, information is available regarding flexibility potentials through the "Smart Energi Hvaler" research project[12].

For the community we define five aggregated load units, where four are flexible, see the left-hand side of Figure 3.5:

- Load shifting of heating in cottages
- Load shifting of water heaters in households
- Load shifting of space heating in households
- Disconnection of low prioritized load in households and commercial buildings
- Inflexible load, representing the residual load

In wintertime, most of the cottages are not in use. However, in order to avoid frost damage, heating is on mainly using space heaters with thermostats. As a part of a research project called DeVID[13], a pilot study is currently being run to analyse the response when disconnecting and when changing temperature set points for heating in cottages. The preliminary results show an average response of 400 W per cottage (Bremdal et al., 2015). In practice, this means that the load can be shifted in time by disconnecting and reconnecting the heating in a cottage. This

[12] www.smartenergihvaler.no

[13] http://www.sintef.no/Projectweb/DeVID/

strategy will delay the load. Likewise, by increasing the temperature set point and later decreasing the temperature set point, it is possible to shift the load to an earlier time. For this load unit, we define four load shift intervals, each consisting of three hours. A total volume must be met within each interval. Our assumption is that 2 500 cottages participate in the load shifting.

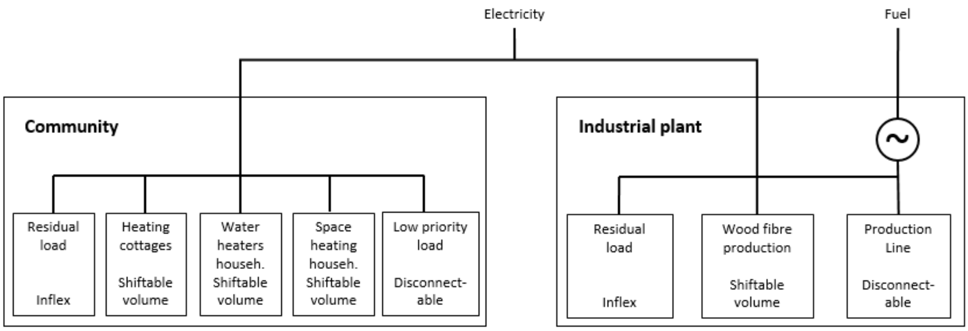


*Figure 3.5. Portfolio energy system*

For households we base our input on findings reported in Graabak & Feilberg (2004), Ericson (2007) and Saele & Grande (2011). We assume that water heaters can be disconnected for up to two hours. By reconnecting, the disconnected volume can be delivered within two subsequent hours. The reported response was on average 500 Wh/h per household. We model this as a shiftable volume load unit where the total flexible volume must be met within a load shift interval consisting of 4 hours. Each household then contributes with 1 kWh volume. We assume that 1 500 households participate. Similarly to the heating of cottages, we define load shifting for space heating in households. Based on reported findings above, we quantify the available volume to 1 kWh/h per household. We assume three load shift intervals of 4 hours and 1 500 households participating.

Finally, we have the low priority load unit, representing different types of loads that can be disconnected and where the volume is not delivered later. Real-life examples are heating without thermostat or fans in office and business buildings. A simple assumption is that 1 MWh/h is available. To illustrate the properties of our model, we constrain the disconnection to last for maximum 3 hours, and with minimum 4 hours between two disconnections. Since a disconnection may lead to disutility, we define a disconnection price of 50 €/MWh.

The industrial plant is based on information from Norske Skog Saugbrugs[14] and Enfo Energy as reported in Roos et al. (2014). We split the load into three load units: One inflexible (1), one shiftable representing wood fibre production (2) and a disconnectable representing a paper production line (3), see the right-hand side of Figure 3.5. For wood fibre production (2) we define a load shift interval covering 24 hours. We assume expected load equal to 5 MWh/h for all 24 hours, and define maximum power to 15 MWh/h, meaning that the expected volume can be met during 8 hours. For the production line (3) we constrain the disconnection to last for maximum 8 hours and with 6 hours as a minimum time between two disconnections. The price for disconnection is 90 €/MWh. The plant is supplied with two different energy carriers: Electricity and fuel. The fuel is input to a converter unit representing electricity generation or steam production. Maximum power output from the converter unit is 5 MW, minimum output when started is 1 MW. Operating the fuel converter costs 90 €/MWh (produced electricity, based on Norwegian prices for fuel oil). We assume start-up costs equal to one MWh generation, i.e. 90 €. When the converter is started, it must operate for at least 3 hours. When it is stopped, it must rest for at least 3 hours before a new start is possible. As a simplification, we model the energy system at the plant as an electricity system, even if some processes in real life are heat based.

Table 3.4 sums up all the flexibility parameters available in our case study:

[14] http://www.norskeskog.com/Business-units/Europe/Norske-Skog-Saugbrugs.aspx

*Table 3.4. Overview of flexibility parameters*

| | | **Total volume** | **Maximum power** | **Load shift intervals** |
|---|---|---|---|---|
| Shiftable community load | Heating cottages | 3.0 MWh | 2.0 MWh/h | 1: hours 7 – 9<br>2: hours 10 – 12<br>3: hours 13 – 15<br>4: hours 16 – 18 |
| | Water heaters households | 1.5 MWh | 0.75 MWh/h | 5: hours 9 – 12<br>7: hours 17 – 20 |
| | Space heating households | 3.0 MWh | 1.5 MWh/h | 5: hours 9 – 12<br>6: hours 13 – 16<br>7: hours 17 – 20 |
| Shiftable ind. plant load | Wood fibre production | 120.0 MWh* | 15.0 MWh/h | 8: hours 1 – 24 |
| | | | | |
| | | **Volume** | **Time constraints** | **Disconnection cost** |
| Curtailable community load | Low priority load | 1.0 MWh/h | Max discon.: 3 h<br>Min rest time: 4 h | 50 €/MWh |
| Curtailable ind. plant load | Production line | 5.0 MWh/h* | Max discon.: 8 h<br>Min rest time: 6 h | 90 €/MWh |
| | | | | |
| | | **Production levels** | **Running time constraints** | **Costs** |
| Industrial plant converter | Fuel converter | Max: 5 MW<br>Min: 1 MW | Minimum running: 3 h<br>Minimum rest time: 3 h | Start-up: 90 €<br>Operation: 90 €/MWh |

* On expectation. This volume is uncertain

## Market and contract conditions

We assume that the aggregator buys all electricity in a spot market, and we use historical price values from Nord Pool Spot in area NO1 as input to our models. We model the balancing market as a penalty, and set a price 5 times the Elspot price. The grid tariff is based on real contract terms for households at Fredrikstad Energi Nett in 2014[15]. The contract terms consist of a fixed fee, that will not influence our decisions, and an energy fee, 46.56 €/MWh, that is equal for all hours. Even if the tariff is flat, it will influence the decisions to disconnect load and to run the fuel converter.

## Process overview

In this case study, we first make scenario trees for spot prices and loads as input to the bidding problem. The forecasting and scenario generation process is presented in Appendix 3.B. Then

[15] http://www.fen.no/default.asp?artid=193

we assume that realizations of the prices and loads do not necessarily follow one single scenario in the scheduling problem.

Figure 3.6 shows an overview of the steps we need to go through in this case study. Each rectangle with ordinary corners represents a process and a model, while the rectangles with snipped corners represent input files.

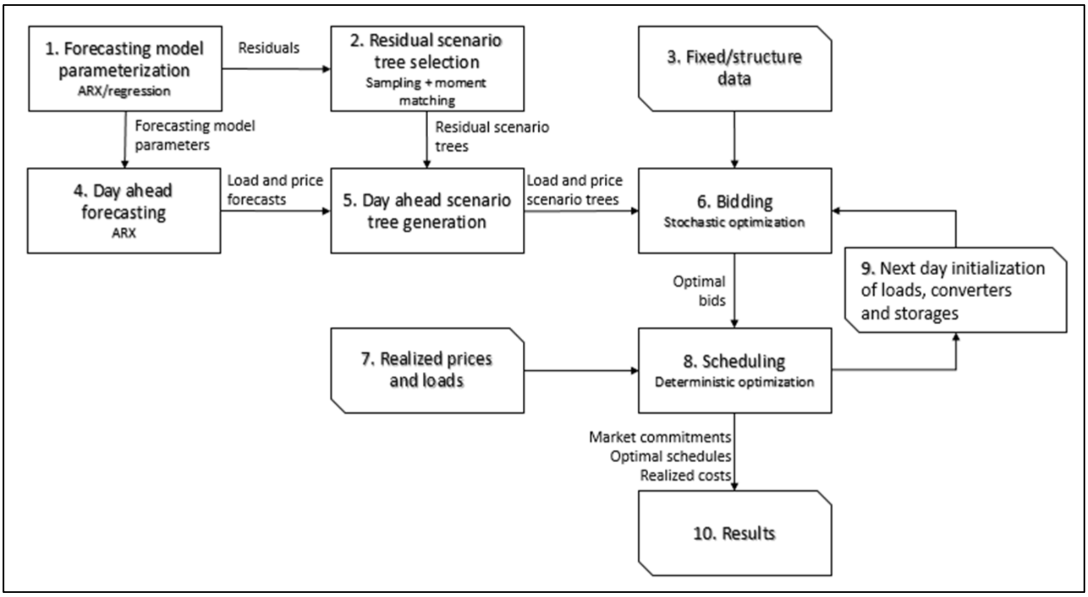


*Figure 3.6. Overview of bidding and scheduling simulation process*

## Results and analysis for one day

In this section we analyse one day in detail. We select January 22$^{nd}$ 2014. The left-hand side of Figure 3.7 shows forecasted and real prices at Nord Pool Spot and forecasted and real total load for the given day. The right-hand side shows the corresponding scenario trees.

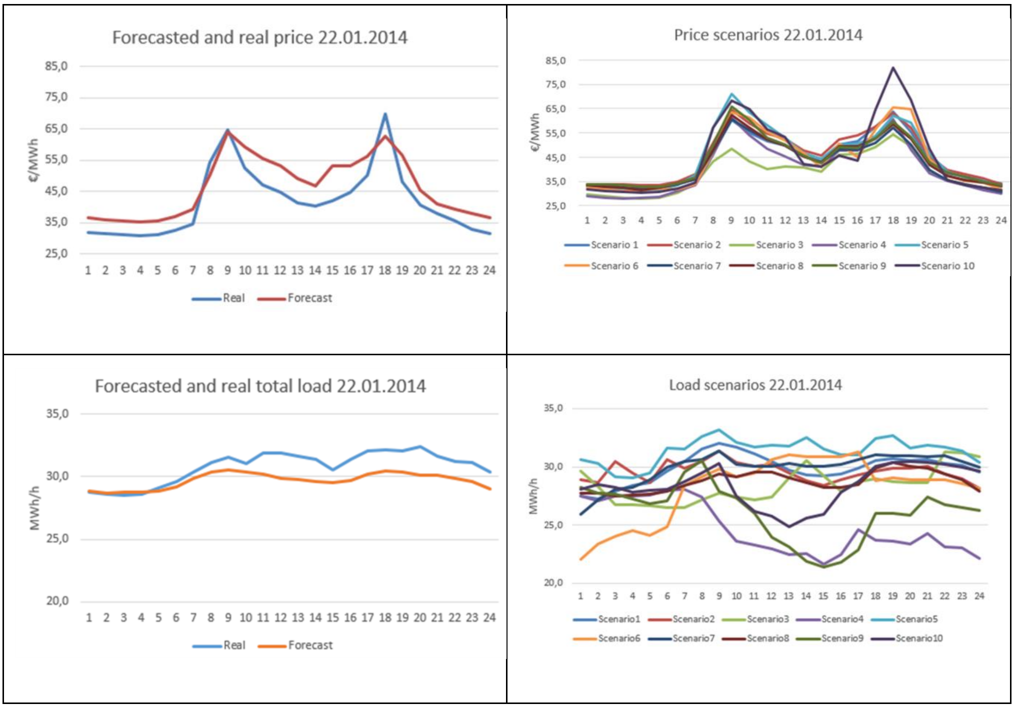


*Figure 3.7. Forecasted and real spot prices and total load with corresponding scenario trees*

Note some observations:

- The price scenarios show a clear pattern with a morning and an afternoon peak. The real prices are inside the scenarios range for all hours.
- The real load is above the forecasted load for almost all hours.
- The load scenarios do not show any clear pattern during the day. The reason is the randomness in the industrial plant, which may stem from technical problems or changes in the production plans. The real load is inside the scenarios for all hours.

Since a precondition for our model is that bid price points are defined exogenously, we need to decide what points to use. It is possible to use up to 64 bid prices, but to reduce calculation times and ease the interpretation of the results, we have decided to limit the number of bid prices to 16. Except from the lower and upper limits, we include prices for the net cost of curtailments and spread the rest of the bid prices evenly in the range where we find the prices for the sampled price scenarios. Then we decide the optimal bid volumes for these prices, see table 3.5.

*Table 3.5. Optimal bid (price points in €/MWh, volume points in MWh)*

| | -500 | 0 | 3 | 4 | 25 | 30 | 35 | 43 | 44 | 50 | 55 | 60 | 65 | 70 | 200 | 3000 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 33.9 | 33.9 | 33.9 | 33.9 | 33.9 | 33.9 | 33.9 | 33.9 | 33.9 | 33.9 | 33.9 | 33.9 | 33.9 | 33.9 | 33.9 | 33.9 |
| 2 | 30.6 | 30.6 | 30.6 | 30.6 | 30.6 | 30.6 | 30.6 | 30.6 | 30.6 | 30.6 | 30.6 | 30.6 | 30.6 | 30.6 | 30.6 | 30.6 |
| 3 | 30.7 | 30.7 | 30.7 | 30.7 | 30.7 | 30.7 | 30.7 | 30.7 | 30.7 | 30.7 | 30.7 | 30.7 | 30.7 | 30.7 | 30.7 | 30.7 |
| 4 | 31.6 | 31.6 | 31.6 | 31.6 | 31.6 | 31.6 | 31.6 | 31.6 | 31.6 | 31.6 | 31.6 | 31.6 | 31.6 | 31.6 | 31.6 | 31.6 |
| 5 | 31.8 | 31.8 | 31.8 | 31.8 | 31.8 | 31.8 | 31.8 | 31.8 | 31.8 | 31.8 | 31.8 | 31.8 | 31.8 | 31.8 | 31.8 | 31.8 |
| 6 | 31.4 | 31.4 | 31.4 | 31.4 | 31.4 | 31.4 | 31.4 | 31.4 | 31.4 | 31.4 | 31.4 | 31.4 | 31.4 | 31.4 | 31.4 | 31.4 |
| 7 | 24.7 | 24.7 | 24.7 | 24.7 | 24.7 | 24.7 | 24.7 | 24.7 | 24.7 | 24.7 | 24.7 | 24.7 | 24.7 | 24.7 | 24.7 | 24.7 |
| 8 | 33.3 | 33.3 | 33.3 | 33.3 | 33.3 | 33.3 | 33.3 | 33.3 | 18.1 | 18.1 | 18.1 | 18.1 | 18.1 | 18.1 | 18.1 | 18.1 |
| 9 | 19.8 | 19.8 | 19.8 | 19.8 | 19.8 | 19.8 | 19.8 | 19.8 | 19.8 | 19.8 | 16.1 | 16.1 | 16.1 | 16.1 | 16.1 | 16.1 |
| 10 | 38.8 | 38.8 | 38.8 | 38.8 | 38.8 | 38.8 | 38.8 | 38.8 | 38.8 | 14.2 | 14.2 | 14.2 | 14.2 | 14.2 | 14.2 | 14.2 |
| 11 | 41.8 | 41.8 | 41.8 | 41.8 | 41.8 | 41.8 | 41.8 | 41.8 | 24.8 | 20.6 | 20.6 | 20.6 | 20.6 | 20.6 | 20.6 | 20.6 |
| 12 | 23.6 | 23.6 | 23.6 | 23.6 | 23.6 | 23.6 | 23.6 | 23.6 | 23.6 | 23.6 | 23.6 | 23.6 | 23.6 | 23.6 | 23.6 | 23.6 |
| 13 | 22.3 | 22.3 | 22.3 | 22.3 | 22.3 | 22.3 | 22.3 | 22.2 | 22.2 | 22.2 | 22.2 | 22.2 | 22.2 | 22.2 | 22.2 | 22.2 |
| 14 | 20.4 | 20.4 | 20.4 | 20.4 | 20.4 | 20.4 | 20.4 | 20.4 | 20.4 | 20.4 | 20.4 | 20.4 | 20.4 | 20.4 | 20.4 | 20.4 |
| 15 | 19.6 | 19.6 | 19.6 | 19.6 | 19.6 | 19.6 | 19.6 | 19.6 | 19.6 | 19.6 | 19.6 | 19.6 | 19.6 | 19.6 | 19.6 | 19.6 |
| 16 | 20.9 | 20.9 | 20.9 | 20.9 | 20.9 | 20.9 | 20.9 | 20.9 | 20.9 | 20.9 | 20.9 | 20.9 | 20.9 | 20.9 | 20.9 | 20.9 |
| 17 | 26.2 | 26.2 | 26.2 | 26.2 | 26.2 | 26.2 | 26.2 | 26.2 | 26.2 | 20.4 | 13.1 | 13.1 | 13.1 | 13.1 | 13.1 | 13.1 |
| 18 | 30.5 | 30.5 | 30.5 | 30.5 | 30.5 | 30.5 | 30.5 | 30.5 | 30.5 | 30.5 | 15.7 | 15.7 | 11.1 | 11.1 | 11.1 | 11.1 |
| 19 | 24.4 | 24.4 | 24.4 | 24.4 | 24.4 | 24.4 | 24.4 | 24.4 | 24.4 | 20.5 | 20.1 | 17.1 | 17.1 | 17.1 | 17.1 | 17.1 |
| 20 | 23.0 | 23.0 | 23.0 | 23.0 | 23.0 | 23.0 | 23.0 | 23.0 | 23.0 | 23.0 | 23.0 | 23.0 | 23.0 | 23.0 | 23.0 | 23.0 |
| 21 | 21.4 | 21.4 | 21.4 | 21.4 | 21.4 | 21.4 | 21.4 | 21.4 | 21.4 | 21.4 | 21.4 | 21.4 | 21.4 | 21.4 | 21.4 | 21.4 |
| 22 | 25.3 | 25.3 | 25.3 | 25.3 | 25.3 | 25.3 | 25.3 | 25.3 | 25.3 | 25.3 | 25.3 | 25.3 | 25.3 | 25.3 | 25.3 | 25.3 |
| 23 | 25.1 | 25.1 | 25.1 | 25.1 | 25.1 | 25.1 | 25.1 | 25.1 | 25.1 | 25.1 | 25.1 | 25.1 | 25.1 | 25.1 | 25.1 | 25.1 |
| 24 | 33.5 | 33.5 | 33.5 | 33.5 | 33.5 | 33.5 | 33.5 | 33.5 | 33.5 | 33.5 | 33.5 | 33.5 | 33.5 | 33.5 | 33.5 | 33.5 |

As expected, we observe that the model uses the flexibility to buy small volumes in the hours where the scenario prices are high (hours 8 – 10 and 17 – 19). We also see that the bids are flat for the hours where the prices vary little between the scenarios (hours 1 – 7, 14 – 16 and 20 – 24), while they are price dependent for the other hours.

Before we decide the optimal schedule, the realized prices and loads are revealed. We then run a deterministic optimization for the scheduling process. Since we penalize imbalances heavily, avoiding imbalances will be a strong driving force.

Realized prices are presented in the upper left part of Figure 3.7. We observe, as expected, that the realizations do not resemble any of the scenarios. According to the submitted bid, the commitments are as presented in the left-hand side of Table 3.6. Note that the Elspot costs are not a part of the objective function of the scheduling model, since Elspot commitments are given from bid decision and prices announced from the market place. Hence, the scheduling model will use internal flexibility to minimize the sum of grid, imbalance, start-up, fuel and curtailment costs. The right-hand side of Table 3.6 shows an overview of the schedules for each of the flexible units. We observe that the decisions fulfil all constraints according to Table 3.4.

*Table 3.6. Optimal market commitments (left) and flexibility schedules for realized prices (right). All values in MWh.*

| | *Committed volume* | *Community* | | | | *Industrial plant* | | |
|---|---|---|---|---|---|---|---|---|
| | | Cottages | Water heaters | Space heating | Low priority | Wood fibre production | Production line | Fuel converter |
| *1* | 33.9 | | | | 0.00 | 10.14 | 0.00 | 0.00 |
| *2* | 30.6 | | | | 1.00 | 11.22 | 0.00 | 3.19 |
| *3* | 30.7 | | | | 1.00 | 9.28 | 0.00 | 1.00 |
| *4* | 31.6 | | | | 1.00 | 14.03 | 0.00 | 5.00 |
| *5* | 31.8 | | | | 0.00 | 15.00 | 5.10 | 2.13 |
| *6* | 31.4 | | | | 0.00 | 15.00 | 5.14 | 2.96 |
| *7* | 24.7 | 0.00 | | | 0.00 | 6.56 | 5.11 | 1.00 |
| *8* | 18.1 | 1.00 | | | 0.00 | 2.14 | 5.08 | 5.00 |
| *9* | 16.1 | 2.00 | 0.00 | 0.00 | 1.00 | 2.36 | 5.16 | 5.00 |
| *10* | 14.2 | 0.16 | 0.75 | 1.50 | 1.00 | 0.00 | 5.07 | 4.67 |
| *11* | 20.6 | 2.00 | 0.50 | 0.00 | 1.00 | 0.50 | 0.00 | 5.00 |
| *12* | 23.6 | 0.84 | 0.75 | 1.50 | 0.00 | 0.00 | 0.00 | 5.00 |
| *13* | 22.2 | 2.00 | | 1.41 | 0.00 | 0.00 | 0.00 | 5.00 |
| *14* | 20.4 | 0.99 | | 0.81 | 0.00 | 0.00 | 0.00 | 5.00 |
| *15* | 19.6 | 0.01 | | 0.00 | 0.00 | 0.00 | 0.00 | 5.00 |
| *16* | 20.9 | 1.00 | | 0.78 | 1.00 | 0.00 | 0.00 | 5.00 |
| *17* | 13.1 | 2.00 | 0.50 | 1.50 | 1.00 | 4.36 | 5.34 | 5.00 |
| *18* | 12.3 | 0.00 | 0.00 | 0.00 | 1.00 | 0.00 | 5.36 | 5.00 |
| *19* | 19.8 | | 0.75 | 0.00 | 0.00 | 4.64 | 5.38 | 5.00 |
| *20* | 23.0 | | 0.75 | 1.50 | 0.00 | 4.42 | 5.54 | 5.00 |
| *21* | 21.4 | | | | 0.00 | 0.42 | 5.35 | 0.00 |
| *22* | 25.3 | | | | 0.00 | 4.77 | 5.33 | 0.00 |
| *23* | 25.1 | | | | 1.00 | 5.83 | 5.43 | 0.00 |
| *24* | 33.5 | | | | 1.00 | 14.86 | 5.38 | 0.00 |

## Quantifying the value of flexibility and the value of stochastic planning

To quantify the value of flexibility in our case study, we perform a simulation over a period of two months spanning from January 1st 2014 to February 28th 2014. We repeat the steps in Figure 3.6 for each day and calculate the cost elements from the scheduling process. We call this the Base case. The key figures are presented in the column named “Base” in the upper left table in Figure 3.9. We observe that the total costs are approximately 3 mill €, where the grid costs are roughly 1/2, Elspot costs 1/3 and the rest consists of costs from imbalances, converter start-ups, fuel and curtailments. Note that despite the available flexibility and high imbalance penalty, imbalance costs have not been completely avoided.

To quantify the value of flexibility, we next remove all flexibility options and rerun the same simulation. The results are presented in the column named “No flex” in the upper left table in Figure 3.9. Since in this case we do not have any flexibility options, we have 0 cost for start-up, fuel and curtailment. The imbalance costs are close to 10 times greater than in the Base case, since we have no flexibility to avoid the imbalances. Note the asymmetry in the imbalances: The consumption surplus is 3.3 times the consumption deficit. The reason for this is that in our calibration period real consumption in the industry is below the forecast (3 % on average), while in the simulation period the real consumption is above the forecast (13 % on average). This means that on average, the model purchases too little compared to real consumption, and we get a consumption surplus situation. The difference in total costs between the two cases are 414 454 € or 12 %. This is the value of flexibility in our case. Due to the high penalty for imbalances, avoiding imbalances is a strong driver. However, note that the model is able to utilize the flexibility to obtain reduced price for buying electricity at Elspot; 0.49 €/MWh reduction on average.

We know that Norwegian electricity prices have small variations during a day compared to most other electricity markets. In order to run the same calculation assuming more volatile prices, we repeat the simulation above, but this time with German prices[16]. Figure 3.8 presents prices in the Norwegian (Oslo area) and German electricity market for January 2014. The mean prices in the two markets are quite equal: 31.7 and 34.8 €/MWh, respectively. However, we observe greater fluctuations in the German market: the variance is 7 times greater than in the Norwegian market. The mean difference between the daily highest and lowest price in Norway for January and February is 10 €/MWh, while in Germany the same figure is 30.

[16] http://www.epexspot.com/en/market-data/auction

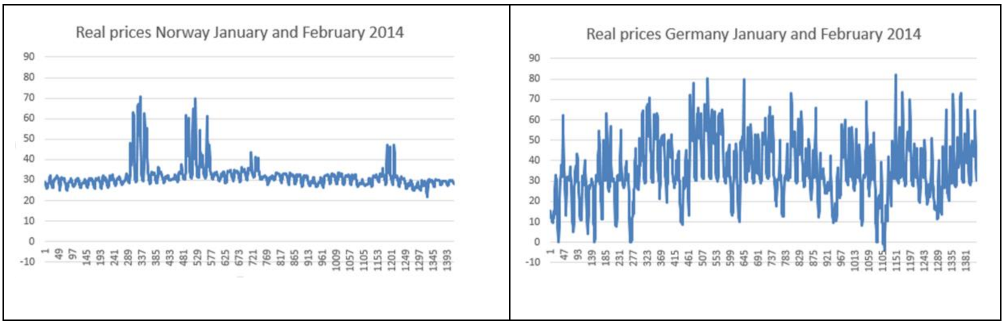


*Figure 3.8. Real prices in Norwegian and German electricity markets January and February 2014*

In the upper right table of Figure 3.9 we see that the value of flexibility based on German prices equals 539 392 €, or 30 % higher compared to the Norwegian case. Note also that the reduction in mean Elspot price for bought electricity is 2.67 €/MWh, which represents a reduction 5 times greater than with Norwegian prices.

Another interesting figure to quantify is the benefit from modelling the uncertainty explicitly compared to planning based on expectation values. We can calculate the value of stochastic planning as suggested in Schütz & Tomasgard (2011). We first calculate the costs from planning based on expected values for prices and loads. Then we compare the costs with the base case. In order to plan based on expected values, we make the following changes in the simulation:

- In the scenario trees, we enter expected values for prices and load for all scenarios
- We use only 2 bid points in the bid and force the bids to be flat to avoid odd effects from the linearization between bid points

The columns Exp. Value in the lower part of Figure 3.9 show the resulting costs from the expectation value simulations.

The left-hand side shows the results based on Norwegian prices. We see that the difference in total cost between the two approaches is 29 693 €, or 1.0 % relative to the expectation value case. This is the value of stochastic planning in our case. For German prices we get 51 514 € and 1.7 %.

As argued earlier, we have defined a high penalty cost in order to force the model to plan into balance and to avoid arbitrage between the markets. For the studies documented in Figure 3.9 we have used 400 % which means that the imbalance price is 5 times the spot price, or approximately 160 €/MWh on average. A crucial question is how the penalty magnitude influences the results. To analyse this, we perform a sensitivity analysis.

**Value of flexibility - Norwegian prices**

| | No flex | Base | Diff | |
|---|---|---|---|---|
| Grid cost: | 1 700 572 | 1 417 794 | 282 778 | € |
| Imbalance cost: | 562 148 | 59 675 | 502 473 | € |
| Startup cost: | 0 | 3 780 | -3 780 | € |
| Fuel cost: | 0 | 261 019 | -261 019 | € |
| Curtailment cost: | 0 | 261 649 | -261 649 | € |
| Elspot cost: | 1 114 302 | 958 651 | 155 651 | € |
| Total cost: | 3 377 022 | 2 962 569 | **414 454** | € |
| Sum volume elspot: | 34 807 | 30 415 | 4 392 | MWh |
| Mean price elspot: | 32,01 | 31,52 | 0,49 | €/MWh |
| Imbalance - consumption surplus: | 2 875 | 226 | 2 650 | MWh |
| Imbalance - consumption deficit: | 881 | 192 | 689 | MWh |

**Value of flexibility - German prices**

| | No flex | Base | Diff | |
|---|---|---|---|---|
| Grid cost: | 1 700 572 | 1 417 638 | 282 934 | € |
| Imbalance cost: | 628 444 | 86 677 | 541 768 | € |
| Startup cost: | 0 | 4 230 | -4 230 | € |
| Fuel cost: | 0 | 274 500 | -274 500 | € |
| Curtailment cost: | 0 | 243 298 | -243 298 | € |
| Elspot cost: | 1 238 851 | 1 002 133 | 236 718 | € |
| Total cost: | 3 567 868 | 3 028 476 | **539 392** | € |
| Sum volume elspot: | 35 010 | 30 628 | 4 382 | MWh |
| Mean price elspot: | 35,39 | 32,72 | 2,67 | €/MWh |
| Imbalance - consumption surplus: | 2 493 | 310 | 2 183 | MWh |
| Imbalance - consumption deficit: | 955 | 494 | 461 | MWh |

**Value of stochastic planning - Norwegian prices**

| | Exp. Value | Base | Diff | |
|---|---|---|---|---|
| Grid cost: | 1 595 764 | 1 417 794 | 177 970 | € |
| Imbalance cost: | 115 961 | 59 675 | 56 285 | € |
| Startup cost: | 3 600 | 3 780 | -180 | € |
| Fuel cost: | 102 991 | 261 019 | -158 028 | € |
| Curtailment cost: | 84 321 | 261 649 | -177 329 | € |
| Elspot cost: | 1 089 625 | 958 651 | 130 974 | € |
| Total cost: | 2 992 262 | 2 962 569 | **29 693** | € |

**Value of stochastic planning - German prices**

| | Exp. Value | Base | Diff | |
|---|---|---|---|---|
| Grid cost: | 1 612 016 | 1 417 638 | 194 378 | € |
| Imbalance cost: | 108 218 | 86 677 | 21 541 | € |
| Startup cost: | 3 510 | 4 230 | -720 | € |
| Fuel cost: | 100 181 | 274 500 | -174 318 | € |
| Curtailment cost: | 80 593 | 243 298 | -162 706 | € |
| Elspot cost: | 1 175 473 | 1 002 133 | 173 340 | € |
| Total cost: | 3 079 991 | 3 028 476 | **51 514** | € |

*Figure 3.9. Value of flexibility (upper) and value of stochastic planning (lower) for Norwegian (left) and German prices (right)*

Table 3.7 presents an overview of the results from simulations over the same two-month period with Norwegian prices. We vary the imbalance penalty from 0 % to 1 000 %.

*Table 3.7. Results from the imbalance penalty sensitivity analysis*

| *Imbalance penalty (%)* | *0* | *10* | *20* | *30* | *50* | *75* | *100* | *200* | *300* | *350* | *400* | *500* | *1000* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Value of flexibility* | 42 659 | 56 809 | 71 539 | 69 780 | 75 198 | 103 328 | 123 991 | 227 753 | 318 064 | 365 024 | 414 454 | 512 095 | 986 108 |
| *Value of stochastic planning* | 2 | 27 752 | 15 765 | 4 696 | -2 016 | -2 539 | -2 261 | 8 132 | 15 506 | 22 375 | 29 693 | 45 232 | 106 560 |

We see that the value of flexibility increases with increasing penalty. Even for 0 penalty the flexibility has a value, since then flexibility is used to exploit price variations between hours and price differences between buying electricity and curtailing load or running fuel converter. When penalty increases, flexibility is also used to avoid imbalance costs. The higher the penalty, the higher amount of the flexibility is used for this purpose.

The value of stochastic planning has a less clear pattern. Irrespective of the penalty level, the base case decides smaller spot volumes and hence lower spot costs compared to the expectation value case. This can be seen from the lower part of Figure 3.7 where we see that the mean value of the load scenarios is smaller than the forecasted load. Next, when the load realizes differently from the bought volumes, the base case strategy is to allow larger imbalances when penalties are small and reduce imbalances by utilizing internal flexibility when penalties are large. For medium penalties, though, this strategy does not pay off compared to the expected value strategy, mainly since the industry load was realized at high levels (higher than expected values).

## Discussion

First a note on the flexibility properties: The shiftable flexibility comes at no cost and may be used to exploit price differences during the day. The disconnectable load units have flexibility at a cost: The community unit has a small volume and a low cost, while the industry has greater volume and higher cost. Unlike the shiftable units, when utilizing the disconnectable ones, we will also save grid costs in addition to spot costs. While the price **variations** are the driver behind the shiftable flexibility, the price **level** is the driver for the disconnectable ones. Finally, we have the fuel converter that represents the highest cost (due to the start-up cost). This source will have the same impact as the disconnectable loads: The price level will be the main driver and utilizing this source will also save grid costs.

Another observation is the asymmetry in the imbalance directions: If the load realizes higher than the volume purchased in the spot market, the energy system has large capability to reduce the load. Disconnecting loads and starting fuel converter will have this effect. In the opposite direction, however, the system has small ability to increase load. The only instrument is to shift the load, which will result in a lower load in other hours. Furthermore, the largest risk for load deviation from forecasted values is a breakdown in the industrial plant, leading to large reduction in load. These properties influence the bid decisions, by bidding lower than the expected load.

Our case study is based on a Norwegian community and a Norwegian industrial plant. In particular the community with its summer cottages is not very representative for other countries. However, other types of consumers may have different sources of flexibility, for instance charging of electric vehicles or air conditioners. One point with our modelling framework is that other types of load units will fit into one of the predefined flexibility classes.

As stated earlier, we have made a set of assumptions and simplifications in our case study. These may have affected the metrics in different ways. First, we have pre-set the bid-points and not updated them for each day dependent on the price scenarios. This simplification may have led to not optimal bids, which in turn can have resulted in too high costs. Second, we have disregarded the possibility to trade in intra-day market, and then removed a possibility to meet imbalances. Our reported imbalance costs may then have been too high. Third, we have treated the imbalance penalty as a certain figure, and not as an uncertain market price that becomes known ex post. It is difficult to say in general what the effect is, since it depends on the imbalance market development. Fourth, we have treated all flexible load as certain in the bidding process. This may also have underestimated the imbalance volumes. Finally, we have simplified the scheduling process by assuming that all figures are known with certainty. In real life this is not the case for loads or from generation from sun and wind. The result is that our imbalance figures may be too low. However, in a real operational situation, this challenge will probably be met with a rolling planning horizon, where the schedules are updated several times a day, each time with more certain information. In our case study, we have assumed a risk neutral aggregator. The asymmetric imbalance situation would probably influence the decisions if we were analysing the situation for a risk averse aggregator. We leave this problem to future research, as well as how asymmetric and uncertain imbalance cost will influence the decisions.

The main purpose with this paper has been to develop optimal decision-support models that fulfil the TSOs' requirement to plan into balance. To illustrate our suggested approach, we have chosen transparent and straightforward forecasting- and scenario generation methods. We have tested the scenario tree stability (in-sample, see Kaut & Wallace (2003)) by generating several scenario trees, running the models and checking the total costs. The analysis indicates stability.

## 3.5. Conclusion and further work

In this paper we propose decision-support models to handle the bidding and scheduling processes for aggregators that supply electricity to prosumers with flexible energy units. We define explicitly the flexibility properties of the underlying energy systems in the prosumers' buildings. Likewise, we include the bidding process and bidding rules and handle the interrelations between hours. Finally, we model the information structure and handle uncertain parameters through scenario trees. Our problem is a two-stage stochastic mixed integer linear program.

The application of the models is illustrated in a case study based on a community and an industrial plant. We obtain a planning process that satisfies all defined constraints. By simulating over a two-month period, we calculate the value of flexibility and the value of stochastic planning. The results indicate a value of flexibility in the order of 12 % of the total costs. Correspondingly, the value of stochastic planning is 1.0 %. Since we expect future electricity market prices to be more volatile, we repeat the calculations also based on German prices and get 15 and 1.7 % respectively. Since a target is to ensure planning into balance, a high penalty cost is defined for imbalances. We find that the values are sensitive to the imbalance penalty, and hence, the numbers must be used with caution.

Future research should handle the imbalance market in more detail. Even other markets where flexibility can be used to create values should be involved, leading to a multi-market model. The information and decision structure will then lead to a multi-stage decision problem.

Future studies which also incorporate tax costs, any low carbon incentives and any other energy related obligations, would also be interesting.

In this paper we analyse one particular business case for the utilization of demand side flexibility: an aggregator participating in the wholesale spot market. We assume that demand side flexibility will have even larger value in solving more local problems in the future smart grid or in ancillary services markets, and hence future research should investigate how to utilize the flexibility in such contexts. Furthermore, an optimal distribution of the profits between the aggregator and each of the prosumers should be elaborated.

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# 3.6. Appendices

## Appendix 3.A. Sets, subsets and indices

| | |
|---|---|
| $T$ | Set of periods, indexed by *t*. |
| $Z \subset T$ | Subset of periods where load curtailment is permitted. |
| $K$ | Set of prosumers, indexed by *k*. |
| $Y$ | Set of internal energy systems, indexed by *y*. An internal energy system is |
| $O$ | Set of energy converter units, indexed by *o*. A converter unit is uniquely connected to one prosumer *k* and one internal energy system *y*. |
| $O^{2w} \subset O$ | Subset of energy converter units that can convert in both directions. |
| $A$ | Set of energy carriers, indexed by *a*. |
| $A^{int} \subset A$ | Subset of energy carriers of type "intermittent". |
| $D$ | Set of load units, indexed by *d*. A load unit is uniquely connected to one prosumer *k* and one internal energy system *y*. |
| $D^{I} \subset D$ | Subset of load units of type "inflexible". |
| $D^{S} \subset D$ | Subset of load units of type "shiftable". |
| $D^{SV} \subset D$ | Subset of load units of type "shiftable volume". |
| $D^{SP} \subset D$ | Subset of load units of type "shiftable profile". |
| $D^{C} \subset D$ | Subset of load units of type "curtailable". |
| $D^{CR} \subset D$ | Subset of load units of type "curtailable reducible". |
| $D^{CD} \subset D$ | Subset of load units of type "curtailable disconnectable". |
| $G$ | Set of possible load shift time intervals, indexed by *g*. |
| $G^{SV} \subset G$ | Subset of possible load shift time intervals for shiftable volume load units. |
| $G^{SP} \subset G$ | Subet of possible load shift time intervals for shiftable profile load units. |
| $L$ | Set of storage units, indexed by *l*. |
| $S$ | Set of scenarios, indexed by *s*. |
| $I$ | Set of bid-points for spot market bidding, indexed by *i*. |
| $B$ | Set of blocks for block bidding in spot market, indexed by *b*. |

## Parameters

| | |
|---|---|
| $R_s$ | Probability for scenario *s*. |
| $P_{t,s}^{spot}$ | Price in spot-market in period *t* and scenario *s* [€/MWh]. |
| $P_t^{grid-import}$ | Price for importing (taking out) electricity from the grid in period *t* [€/MWh]. |
| $P_t^{grid\text{-}export}$ | Price for exporting (feeding in) electricity to the grid in period *t* [€/MWh]. |
| $P_o^{startup}$ | Start-up cost for converter *o* [€]. |
| $P_a^{fuel}$ | Price for energy carrier *a* [€/kWh]. |
| $P_d^{curtail}$ | Disutility cost for curtailment of load unit *d* [€/kWh]. |
| $P_t^{imbal}$ | Penalty for not meeting committed volume in period *t* [€/MWh]. |
| $P_i^{bid}$ | Price at bid-point *i* for bidding to spot-market [€/MWh]. |
| $T_b^{start}$ | Start period for block *b*. |
| $T_b^{end}$ | End period for block *b*. |
| $W_{d,t,s}$ | Load forecast for load unit *d* in period *t* and scenario *s* [kWh/period]. |
| $T_g^{start}$ | Earliest possible start period for load shift time interval *g*. |
| $T_g^{end}$ | Latest possible end period for load shift time interval *g*. |
| $V_g^{start}$ | Start-period for load forecast for load shift time interval *g*. |
| $V_g^{end}$ | End-period for load forecast for load shift time interval *g*. |
| $B_d^{max}$ | Max number of reductions for curtailable load unit *d* during the planning horizon [#]. |
| $D_d^{max}$ | Maximum duration of a curtailment for curtailable load unit *d* [# of periods]. |
| $D_d^{min}$ | Minimum duration between two curtailments for curtailable load unit *d* [# of periods]. |
| $U_d^{max}$ | Maximum fraction available for reduction in reducible load unit *d*. |
| $X_d$ | Disutility cost for curtailed load for load unit *d* [NOK/kWh]. |
| $E_d^{max}$ | Maximum power for shiftable volume load unit *d* [kW]. |

| | |
|---|---|
| $E^{min}_{d,t}$ | Minimum power for shiftable volume load unit *d* in time period *t* [kW]. |
| $G^{max}_{o}$ | Maximum output from converter unit *o* [kW]. |
| $G^{min}_{o}$ | Minimum output (when started) from converter unit *o* [kW]. |
| $A_{o}$ | Efficiency function for converter unit *o*. |
| $J^{min\text{-}up}_{o}$ | Minimum up-time when started for converter unit *o*. |
| $J^{min\text{-}down}_{o}$ | Minimum down-time when stopped for converter unit *o*. |
| $C^{ramp-up}_{o}$ | Maximum positive change of output between two periods for converter unit *o*. |
| $C^{ramp-down}_{o}$ | Maximum negative change of output between two periods for converter unit *o*. |
| $I_{o,t,s}$ | Forecasted supply of intermittent energy carrier to converter *o* in time period *t* and scenario *s* [kWh]. |
| $O^{max}_{l}$ | Maximum storage capacity for storage unit *l* [kWh]. |
| $Q^{in}_{l}$ | Maximum charging capacity for storage unit *l* [kW]. |
| $Q^{out}_{l}$ | Max discharging capacity for storage unit *l* [kW]. |
| $A^{in}_{l}$ | Efficiency factor for charging storage unit *l*. |
| $A^{out}_{l}$ | Efficiency factor for discharging storage unit *l*. |
| $H_{l}$ | Minimum state of charge for storage unit *l* at the end of planning horizon. |

## Variables

| | |
|---|---|
| $\chi^{spot}_{t,s}$ | Total amount of electricity purchased at the spot market in period *t* in scenario *s* [MWh]. |
| $\chi^{com}_{t,s}$ | Amount of electricity purchased at the spot market on single period bids in period *t* in scenario *s* [MWh]. |
| $\bar{\chi}^{com}_{b,s}$ | Amount of electricity purchased at the spot market on block bids in period *t* in block *b* in scenario *s* [MWh]. |
| $\chi^{total-import}_{t,s}$ | Total amount of electricity imported (taken out) from the grid in period *t* in scenario *s* [MWh]. |
| $\chi^{total\text{-}export}_{t,s}$ | Total amount of electricity exported (fed in) to the grid in period *t* in scenario *s* [MWh]. |

| | |
|---|---|
| $\chi_{t,s}^{imbal}$ | Volume difference between committed in spot market and real exchanged in period *t* in scenario *s* [kWh]. |
| $\kappa_{t,s}^{startup}$ | Costs for starting up converter units in period *t* in scenario *s* [€]. |
| $\kappa_{t,s}^{fuel}$ | Fuel costs for running converter units in period *t* in scenario *s* [€]. |
| $\kappa_{t,s}^{curtail}$ | Costs for curtailing load units in period *t* in scenario *s* [€]. |
| $\chi_{i,t}^{bid}$ | Volume bid by hourly bid to the spot market at bid-point *i* in time period *t* [MWh]. |
| $\overline{\chi}_{i,b}^{bid}$ | Volume bid by block bid to the spot market at bid-point *i* in block *b* [MWh]. |
| $\chi_{k,a,t,s}$ | Amount imported to prosumer *k* of energy carrier *a* in period *t* in scenario *s* [kWh]. |
| $\varphi_{d,t,s}$ | Amount of energy curtailed from reducible load unit *d* in period *t* in scenario *s* [kWh]. |
| $\alpha_{o,t,s}^{start}$ | Binary variable = 1 if converter unit *o* is starting in the beginning of period *t* in scenario *s*, else 0. |
| $\chi_{a,o,t,s}$ | Amount of energy carrier *a* imported to converter unit *o* in period *t* in scenario *s* [kWh]. |
| $\psi_{o,t,s}$ | Amount of energy produced from converter unit *o* in period *t* in scenario *s* [kWh]. |
| $\varphi_{d,t,s}$ | Amount of energy reduced from reducible load unit *d* in period *t* in scenario *s* [kWh]. |
| $\omega_{d,t,s}$ | Delivered energy to shiftable load unit *d* in period *t* in scenario *s* [kWh]. |
| $\sigma_{l,t,s}^{in}$ | Energy charged to storage unit *l* in period *t* in scenario *s* [kWh]. |
| $\sigma_{l,t,s}^{out}$ | Energy discharged from storage unit *l* in period *t* in scenario *s* [kWh]. |
| $\sigma_{l,t,s}^{soc}$ | State of charge for storage unit l in period t in scenario s [kWh]. |
| $\delta_{d,t,s}^{start}$ | Binary variable = 1 if curtailment of curtailable load unit *d* starts in the beginning of period *t* in scenario *s*, else 0. |
| $\delta_{d,t,s}^{run}$ | Binary variable = 1 if curtailment of load unit *d* is running in time period *t* in scenario *s*, else 0. |
| $\delta_{d,t,s}^{end}$ | Binary variable = 1 if curtailment of curtailable load unit *d* ends in the end of period *t* in scenario *s*, else 0. |
| $\alpha_{o,t,s}^{start}$ | Binary variable = 1 if operation of converter unit *o* is starting in the beginning of period *t* in scenario *s*, else 0. |

| | |
|---|---|
| $\alpha_{o,t,s}^{run}$ | Binary variable = 1 if operation of converter unit *o* is running in period *t* in scenario *s*, else 0. |
| $\alpha_{o,t,s}^{end}$ | Binary variable = 1 if operation of converter unit *o* stops in the end of time period *t* in scenario *s*, else 0. |
| $\gamma_{g,i,s}$ | Binary variable = 1 if load for load shift interval *g* is moved *i* periods in scenario *s*, else 0. |

## Appendix 3.B. Forecasting and scenario generation

Our case study contains three types of uncertain parameters:

- Elspot prices
- Load at the community
- Load at the industrial plant

We will make scenario trees for these uncertain parameters. Our approach is to start from a forecasted value and add variation in the scenarios by sampling from the residual time series (the difference between the forecasted and realized values).

For the industrial plant, we have access to forecasts and residuals directly. For Elspot prices and community load we need to develop forecasting models. There are many ways to forecast prices and loads. In our study we need a model that can provide proper input to the scenario trees. A rather straightforward forecasting method is selected, and we choose the same approach both for price and load forecasting.

Our starting point is the ARX-model proposed by Weron (2007) which is further elaborated and used at Nord Pool Spot-prices by Kristiansen (2012). We include 4 AR-components referring to one day, two days, a week and the previous day's maximum or minimum-value. The exogenous components are three variables for days in the week: one for Saturday, one for Sunday and one for Monday. Finally, we have one exogenous explanatory variable related to fundamental conditions. In the price model we use forecasted total load in Norway, as published by Nord Pool. For the load model we use forecasted outdoor temperature. By doing so, we base our forecasts only on information that is known at the time of the decision.

In general, we formulate the forecasting model as follows:

$$v_t = \varphi_1 v_{t-24} + \varphi_2 v_{t-48} + \varphi_{168} v_{t-168} + \varphi_4 mv_t + \psi f_t + d_1 D_{Mon} + d_2 D_{Sat} + d_3 D_{Sun} + \varepsilon_t, \tag{3.37}$$

where

| | |
|---|---|
| $v_t$ | The variable to be forecasted |
| $v_{t-24}, v_{t-48}, v_{t-168}$ | Real value for the variable 24, 48 and 168 hours back |
| $\varphi$ | Parameters for the AR components |

| | |
|---|---|
| $mv_t$ | Maximum value for the variable previous day |
| $\psi$ | Parameter for exogenous fundamental variable |
| $f_t$ | Value of exogenous fundamental variable |
| $d_1, d_2, d_3$ | Parameters for day-variables |
| $D_{mon}, D_{sun}, D_{sat}$ | Dummy variables for Monday, Saturday and Sunday. $D_{mon}$ = 1 if t belongs to a Monday, else 0 |
| $\varepsilon_t$ | Residual value |

We have chosen to generate one common set of parameters valid for all hours. A possible improvement is to generate 24 separate parameter sets, one for each hour.

For both forecasting models we parameterize based on historic values for the period 01.01.2012 to 31.12.2013, and evaluate the model for the period 01.01.2014 to 30.04.2014.

For the load-forecasting model we obtain a mean absolute percentage error (MAPE) equal to 5.8 %. The corresponding result is 13.0 % for the price-forecasting model. Both produce residuals that are strongly auto correlated, with correlation factors equal to 0.95 and 0.7, respectively. The reason for this is that when we forecast for all hours one day ahead, fundamental conditions will influence the price and load for several hours. Hence, the residuals cannot be considered as white noise.

The same situation is valid for the industrial plant, where we see a 0.9 autocorrelation for the residuals, which in this case are the real imbalances. Fundamental conditions are the explanation also here, for instance a technical failure in the factory (leading to lower load) or a repair of a failure that is ready earlier than expected (leading to higher load).

Since residuals for each type of data are autocorrelated, we conclude that we cannot sample for two hours independently when we are going to generate scenario trees.

By analysing the residuals for the prices, the community load and the industrial plant load, we find no cross-correlations. The factors vary between -0.01 and 0.04. We then conclude that we can sample residuals to the scenario tree for one type of data independent from the other types.

When we are going to sample residuals for one data type, we want the scenario tree to have statistical properties similar to the full residual series. We ensure the autocorrelation by picking residuals for all 24 hours for each sample. In addition, we follow the principle for property matching defined by Seljom & Tomasgard (2015). We start out by removing residuals for months that are far away from the period we are analysing. Since we want to analyse days in January and February, we keep the values for December, January, February and March. Then we group the residuals into two: One group for working days and one for non-working days (Saturdays, Sundays and public holidays). For each of these groups and for each hour of the day, we calculate the first four statistical moments: Mean, variance, skewness and kurtosis. Next, we sample 10 random series from the correct group. We calculate the 4 moments for this scenario tree for each hour. Then we calculate the deviation:

$$D = \sum_{p=1}^{24} \sum_{m=1}^{4} abs\left[ \frac{M_{p,m}^{total} - M_{p,m}^{scenariotree}}{M_{p,m}^{total}} \right] \tag{3.38}$$

For each hour and moment we calculate the absolute value of the relative difference between the total series and the scenario tree. We calculate the total deviation as the sum of deviations over all hours and moments. This process is repeated until D is smaller than a predefined tolerance gap. Then we keep this scenario tree and use it for one day. The scenario generation process is repeated for each day.

We repeat this sampling process for each type of data, resulting in a scenario tree with information about prices, community load and industrial plant load.

Finally, in order to take into consideration the risk of extreme events, we include one extreme high scenario and one extreme low scenario. We pick these from the days with greatest and smallest residuals in the sampling period. In the scenario tree we allocate 0.5 % probability to each of the extreme scenarios. For the scenarios from the sampling process, we allocate 99 % probability equally distributed to each scenario.

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Paper 3

Stig Ødegaard Ottesen, Asgeir Tomasgard and Stein-Erik Fleten:

# *Multi market bidding strategies for demand side flexibility aggregators in electricity markets*

*Submitted to international, peer-reviewed journal*

# Chapter 4. Multi market bidding strategies for demand side flexibility aggregators in electricity markets

## Abstract

Due to the electricity systems' increasing need for flexibility, the concept of demand side flexibility aggregation becomes more important. In this paper, we propose a coordinated bidding strategy for a flexibility aggregator with the objective to maximize the profit from a flexibility portfolio by participating in three sequential markets. We demonstrate the approach in a generalized market design that is flexible enough to capture today's market structure and still relevant in the next generation market design, both at wholesale and local level: an options market where flexibility is reserved for later use, a spot market for energy day-ahead or shorter, and a flexibility market where flexibility units are dispatched near real-time. Since the bidding decisions are made sequentially and the price information is gradually revealed, we formulate the problems as multi-stage stochastic programs. To ensure feasible operational schedules, the flexibility units are modelled with technical constraints. We illustrate the application of the models by performing a realistic case study in cooperation with four industrial companies and one aggregator, simulating participation in the Norwegian wholesale markets. In the case study we quantify and discuss the value of flexibility and the value of aggregation.

## 4.1. Introduction

Due to the growing share of intermittent generators connected at various voltage levels, electrification of the transport sector and the development of new consumption patterns, the electricity systems face an increased need for flexibility (Eurelectric, 2014; GEODE, 2014; European Commision, 2015). Eurelectric defines flexibility as "*the modification of generation injection and/or consumption patterns in reaction to an external signal (price signal or activation) in order to provide a service within the energy system. The parameters used to characterize flexibility in electricity include: the amount of power modulation, the duration, the rate of change, the response time, the location etc*". Since most of the above mentioned changes come at the distribution grid level, the flexibility is in particular needed at the demand side.

In order to exploit the flexibility potential of smaller customers, the concept of aggregation is important (Eurelectric, 2014). An aggregator role can function as an intermediate between smaller customers and the market, and hence on one side can offer market access for the smaller customers and on the other side can offer increased flexibility volumes to the electricity market.

Also ENTSO-E[17] supports the idea above by stating that "*The demand side should participate as much as possible in all markets*" (ENTSO-E, 2014). To accomplish this, they suggest that market rules are amended to enable the work of aggregators.

In response to the increased need for flexibility, a large number of concept studies and demonstration activities related to market design changes have been initiated. Some focus on the change of rules in existing, while others introduce new markets.

The ECO-Grid project proposes a new, local real-time market to balance the power system. The market place repeatedly issues a real-time price signal for flexible resources to respond to (Gantenbein et al. (2012). A neighbourhood market is proposed in the Nobel-project (Ilic et al. (2012) aiming at trading locally produced renewable generation. The iPower project introduces a clearinghouse for flexibility services (FLECH) at the distribution level (Ding et al., 2013; Heussen et al. (2013). They distinguish between reservation and scheduling of flexibility

[17] European network of transmission system operators for electricity, www.entsoe.eu

services. This idea is also supported by Rosen & Madlener (2014), who propose a weekly auction for reservation of capacity for every hour of the days in the following week.

The ongoing Horizon 2020-project EMPOWER[18] elaborates a local market concept with three basic types of markets: One for local energy, one for local flexibility and one for other services (Ilieva et al. (2016).

The initiatives mentioned above are all European. However, similar initiatives are ongoing all over the world. The most relevant one is perhaps the Reforming Energy Vision (REV) in New York (MDPT Working Group, 2015).

In this article we define a market design which is a synthesis of the work referenced above:

- An options market (OM), where flexibility capacity is reserved for potential later use. The trading horizon is several days.
- A spot market (SM), where electricity is traded for the day-ahead (or shorter) with a time granularity of one hour or less.
- A flexibility market (FM), where flexibility is activated in real time or close to real time.

Note that this market framework is partly similar to already existing electricity markets at the wholesale level. One example is the Norwegian market regime, where Statnett's[19] Tertiary reserves options market ("RKOM uke"), Nord Pool's[20] Elspot day-ahead market and Statnett's Tertiary reserves market ("RK"), correspond to the OM, SM and FM, respectively.

Bidding decisions for multiple, sequential electricity markets have been studied in a small number of papers, all seen from the perspective of a power producer. A literature review regarding this topic is given in Klæboe & Fosso (2013). They state that *"From a theoretical point of view, the optimal bidding strategy will be found by taking all subsequent markets into account when bidding in the first market"*. First, they review the bidding models, all covering day-ahead market in different combinations with intraday, balancing and ancillary services

[18] Local Electricity Retail Markets For Prosumer Smart Grid Power Services, www.empowerh2020.eu

[19] Statnett is the Norwegian transmission system operator, see www.statnett.no/en

[20] www.nordpoolspot.com

markets (Boomsma, Juul, & Fleten, 2014; Faria & Fleten, 2009; Löhndorf & Minner, 2010; Plazas, Conejo, & Prieto, 2005; Triki, Beraldi, & Gross, 2005). *Coordinated bidding* is the term they use when taking subsequent markets into account, while the contrary is denoted *separate bidding*. Just a few studies quantify the gain from coordinated bidding. Although these figures are not very high (0,1 to 2%), the gain is expected to increase with increasing price differences between the markets (Boomsma et al., 2014).

The problem we consider in this paper has many similarities with the multi-market bidding studies referenced above. We also use the concept of coordinated bidding. However, our focal entity is not a power producer, but a demand side flexibility aggregator. Contrary to the studies above, we also include the OM, where capacity is reserved for later use in FM. To our knowledge this has not been covered before. Furthermore, we also take into account the fact that in a real world setting, the prices will hardly realize according to the predefined scenarios.

Our starting point is the previous work (Ottesen, Tomasgard, & Fleten, 2016), where we developed a bidding and scheduling model for day-ahead market participation for an aggregator. The main objective for the aggregator was to minimize expected costs for supplying electricity to a set of prosumers, while dispatching flexible energy units. Our extension compared to the previous work is that the aggregator is managing the flexibility explicitly and maximizing profit by allocating optimal volumes to the three markets. Since the bidding is sequential in these markets and the prices are gradually realized, we formulate the bidding problems as multistage, stochastic programs.

The contribution from this article is four-fold:

- We develop a mixed integer multi-stage stochastic programming model for coordinated bidding to determine optimal bidding strategies for a flexibility aggregator participating in three sequential markets, including a market for reservation of capacity
- We model explicitly the information revelation process, and take into account that prices may realize differently from the scenarios
- To ensure technically feasible solutions, we put effort into modelling the flexibility units properly to capture physical and economic constraints in the underlying, physical systems

- We perform a realistic case-study based on 4 industrial companies and one aggregator including a quantification and discussion of the value of flexibility and the value of aggregation

The remainder of the paper is organized as follows: Section 4.2 outlines the problem, including descriptions of the trading process and the information structure. The mathematical formulations are presented in Section 4.3, while Section 4.4 contains the case study.

## 4.2. Problem description

### Flexibility and market design

Let a flexibility aggregator manage a portfolio of flexibility units on behalf of a set of flexibility vendors. The flexibility aggregator's objective is to maximize the profit from the portfolio by trading in a set of markets. Each flexibility vendor has at least one flexibility unit, which can provide services for up-regulation or down-regulation. A flexibility unit represents an appliance or a group of appliances that can alter the electricity produced or consumed. In other words, a flexibility unit can represent controllable loads, generators and storages. Although we in this paper focus only on flexibility, we follow the same principles as in our previous work (Ottesen et al., 2016) and split flexibility units into discrete units (that can only be switched on or off), continuous units (that can be regulated up or down continuously) and shiftable units (that can be regulated in both directions, but where a net volume constraint must be fulfilled within a set of periods). In addition, we define parameters for maximum and minimum duration of a regulation and minimum rest-time between two regulations.

Each flexibility unit has a capability for regulating up or down in each time period. Up-regulation means increased generation or reduced load, while down-regulation is the opposite. This definition is in line with existing terminology used in balancing markets (Wangensteen, 2011; Bollen, 2011).

Up-regulation means selling to the market, and this action comes to an added cost for the flexibility vendor. For a generator, up-regulation cost can be related to extra use of fuel. The cost for reducing load may be related to added cost of alternative solutions, reduced volume of produced goods or loss of comfort. Up-regulation is profitable for the flexibility vendor if the income from selling to the market exceeds the cost for performing the up-regulation activity.

For down-regulation it is a bit different. Reduced generation or increased load means buying from the market. This action comes to a reduced cost, for example reduced use of fuel or increased volume of produced goods. Hence, down-regulation is profitable if the added cost from buying in the market is smaller than the reduced cost from performing the down-regulation. In many cases the reduced cost is 0, and down-regulation is profitable only if the market prices are negative.

The aggregator's task is to maximize the value of the flexibility portfolio by trading in three sequential markets as illustrated in Figure 4.1.

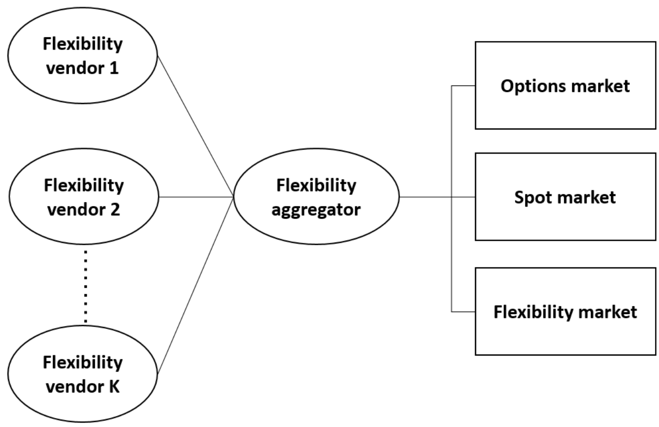


*Figure 4.1. Flexibility vendors, aggregator and markets*

For the ease of exposition, we use one week as the trading horizon for the OM, one day for the SM and the FM and one hour as the time granularity in all markets. Such a market framework can cover different market regimes on different levels. On one side it can cover capacity markets, day-ahead markets and real-time/balancing markets at the wholesale level. On the other hand, it can cover future local markets at the distribution grid level.

In this article we assume step-wise bid-formats for the OM and the FM, while the SM has piece-wise linear bidding curves (see for instance Boomsma et al. (2014)). Further, we assume that all markets are settled according to pay-as-clear principle, also denoted uniform price, as opposed to pay-as-bid (Oren, 2004). However, other bid formats and settlement principles will not change the basic approach.

## The trading process and decision making under uncertainty

The trading process will be sequential: First, the aggregator submits a bid to the OM for one week. The market operator clears the market and publishes the OM prices and commitments. Second, the aggregator submits a bid to the SM for the first day in the week. The market operator clears the market and publishes the SM prices and commitments. Third, the aggregator submits a bid to the FM for the first hour. The market operator calls for activations and publishes the FM price. This process is illustrated in Figure 4.2.

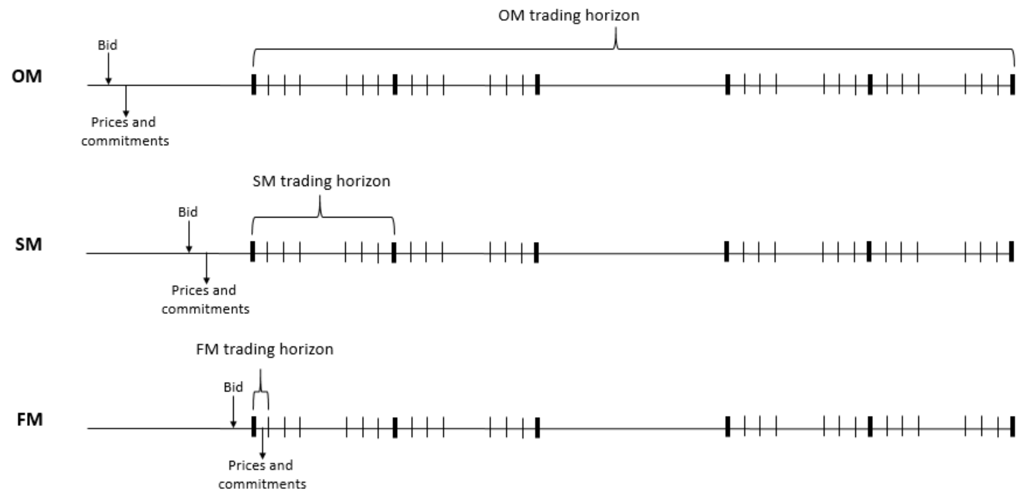


*Figure 4.2. Illustration of the bidding and market clearing process*

Next, the process for the FM continues to the next hour, repeatedly until the last hour for that day. Then the SM trade moves to the next day, the FM trade starts for the first hour, then the second hour and so forth. When the FM is finished for the last hour in the week, the OM is cleared for the consecutive week.

The aggregator's problem is to decide the bids to each of the markets so that the expected profit is maximized. Since the prices are revealed gradually, these decisions must be made under uncertainty.

As illustrated in Figure 4.2 the aggregator receives new price information 176 times a week (one for the OM, seven for the SM and 168 for the FM). According to stochastic programming theory (Birge & Louveaux, 2011; Conejo, Carrión, & Morales, 2010; Kall & Wallace, 1994), we might model the process as a 176 stages' scenario tree, where a decision is made in each stage and new information is revealed between two stages. However, in order to make the problem mathematically tractable, we simplify by assuming that all FM prices and commitments are published once a day. Further, we reduce the number of stages to three.

We establish a new scenario tree for each bid decision and implement only the first stage decision. The other stages are included just to capture their impact on the first stage decision. Figure 4.3 illustrates a three-stage scenario tree.

The objective for the OM problem is to maximize expected profit for the whole OM trading horizon (one week). The optimal bid volume to the OM depends on the balance between expected profits from the OM and the FM versus the expected profits from the SM for the same trading horizon. The OM bid decision is made in the first stage. Then the OM prices are revealed. In the second stage, the SM bid decision and allocation to the FM are made. Then the SM and FM prices are revealed. Finally, in the third stage the scheduling decision is made. The aggregator submits the OM bids and receives the realized OM prices and corresponding commitments.

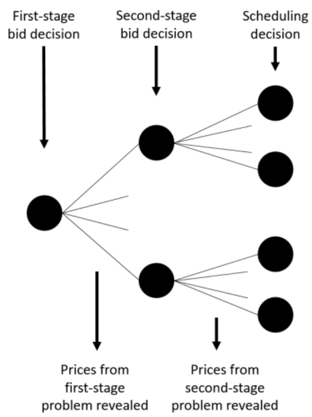


*Figure 4.3. Three-stage scenario tree*

Next, we move to the SM problem and establish a new three-stage scenario tree. The objective for the SM problem is to decide a SM bid that maximizes the expected profit for the SM trading horizon (one day). The optimal decision depends on the balance between expected profits from the SM and the FM markets, constrained by the OM commitment and the flexibility units. The SM bid decision is made in the first stage. Then the SM prices are revealed. In the second stage the FM bid decision is made and the FM prices are revealed. Further, in the third stage, the scheduling decision is made. The aggregator submits the SM bids and receives the realized SM prices and corresponding commitments.

Then we establish the FM problem. The objective for the FM problem is to decide a FM bid that maximizes expected profit, taken into account commitments from the OM and SM markets and the flexibility unit constraints. In the first stage, the FM bid decision is made. Then the FM prices are revealed. In the second stage, the scheduling decisions are made. Note that the FM problem is handled in a two-stage scenario tree. The aggregator submits the FM bids and receives the realized FM prices and corresponding commitments.

The final problem for the aggregator is to decide schedules for each flexibility unit. Since all prices and commitments are known with certainty, this problem is deterministic.

In this article we assume that the aggregator is risk neutral and a price taker.

## 4.3. Mathematical formulation

In this section we outline the mathematical formulation for the bidding and scheduling problems, with one section for each problem type. We describe the sets, parameters and variables successively as they appear. A full list is found in Appendix 4.A.

### The OM problem

#### Objective function

The objective in the OM problem is to maximize the expected total profit over the OM planning horizon $t \in T^1$, where superscript *1* denotes the OM market:

$$\max z^1 = \sum_{s \in S} R_s \left[ \sum_{t \in T^1} \begin{Bmatrix} P_{1,t,s}^{up} \gamma_{1,t,s}^{up} + P_{1,t,s}^{down} \gamma_{1,t,s}^{down} + P_{2,t,s} (\gamma_{2,t,s}^{up} - \gamma_{2,t,s}^{down}) \\ + P_{3,t,s} (\gamma_{3,t,s}^{up} - \gamma_{3,t,s}^{down}) - \kappa_{t,s}^{up} + \kappa_{t,s}^{down} \end{Bmatrix} \right]. \tag{4.1}$$

$R_s$ is the probability for scenario *s*. The first term $P_{1,t,s}^{up}\gamma_{1,t,s}^{up}$ represents the revenues from reservation of up-regulation in the OM market calculated by multiplying the price for reservation $P_{1,t,s}$ in period *t* in scenario *s* with the corresponding commitment $\gamma_{1,t,s}^{up}$. Similarly, $P_{1,t,s}^{down}\gamma_{1,t,s}^{down}$ is the revenue from reserving down-regulation volumes. We assume separate prices for reservation of up- and down-regulation, since volumes can be reserved for both directions in the same period. The second and third terms represent revenues and cost from the SM (market 2) and FM (market 3), respectively. Similar to the OM revenue, $P_{2,t,s}\gamma_{2,t,s}^{up}$ represents the revenue from up-regulation in the SM, while $-P_{2,t,s}\gamma_{2,t,s}^{down}$ represents the cost for down-regulation. The same applies for the FM.

For each regulation unit we calculate the up-regulation added cost as the product of unit regulation added cost $P_u^{up}$ for regulation unit *u* and volume regulated up $\varphi_{u,t,s}^{up}$ in period *t* and scenario *s*. The total aggregated up-regulation added cost $\kappa_{t,s}^{up}$ in period *t* and scenario *s* is the sum of up-regulations over all units *u* and all flexibility vendors *k*.

$$\kappa_{t,s}^{up} = \sum_{k \in K} \sum_{u \in U(k)} P_u^{up} \varphi_{u,t,s}^{up}, \quad t \in T^1, s \in S. \tag{4.2}$$

Likewise, when we regulate down, we calculate the total aggregated reduced costs $\kappa_{t,s}^{down}$ as the sum of down-regulation reduced cost over all units *u* and all flexibility vendors *k*.

$$\kappa_{t,s}^{down} = \sum_{k \in K} \sum_{u \in U(k)} P_u^{down} \chi_{u,t,s}^{down}, \quad t \in T^1, s \in S. \tag{4.3}$$

## Bid constraints

The OM bid format is step-wise, and the bid constraint is formulated as:

$$\gamma_{1,t,s}^{up} = \chi_{1,i,t}^{up}, \quad P_{1,i} < P_{1,t,s} \le P_{1,i+1}, \; i \in I^1, t \in T^1, s \in S, \tag{4.4}$$

where $\chi_{1,i,t}^{up}$ is bid volume at bid point $i$. According to the bidding rules, the volume points must be non-decreasing with increasing price:

$$\chi_{1,i,t}^{up} \ge \chi_{1,i-1,t}^{up}, \quad i \in I^m, i \ne 1, \; t \in T^1. \tag{4.5}$$

## Market commitment constraints

Scheduled regulations $\varphi_{u,t,s}^{up}$ summed over all regulation units *u* and flexibility vendors *k* must equal committed volumes to the SM and the FM in each period *t* and scenario *s*:

$$\sum_{k \in K} \sum_{u \in U} \varphi_{u,t,s}^{up} = \gamma_{2,t,s}^{up} + \gamma_{3,t,s}^{up}, \quad t \in T^1, s \in S. \tag{4.6}$$

$$\sum_{k \in K} \sum_{u \in U} \varphi_{u,t,s}^{down} = \gamma_{2,t,s}^{down} + \gamma_{3,t,s}^{down}, \quad t \in T^1, s \in S. \tag{4.7}$$

## Flexibility constraints

All regulation units $u \in U$ will have a maximum regulation capability per period for up $W_{u,t}^{up}$ and down $W_{u,t}^{down}$, respectively. The scheduled regulation at each regulation unit must be equal to or lower than the capability:

$$\varphi_{u,t,s}^{up} \le W_{u,t}^{up}, \quad u \in U, t \in T^1, s \in S. \tag{4.8}$$

$$\varphi_{u,t,s}^{down} \le W_{u,t}^{down}, \quad u \in U, t \in T^1, s \in S. \tag{4.9}$$

### Non-anticipativity constraints

We have used a variable splitting formulation where a copy of each of the first- and second-stage variables exist for each scenario. Non-anticipativity constraints (Kall & Wallace, 1994) are then needed to ensure that the first-stage variables take the same values in all scenarios. Further, the second-stage variables that belong to the same subset of scenarios must also take the same values. Since the OM bid decision is independent of scenario, the OM bid constraint automatically fulfils non-anticipativity constraint for the first-stage. For the second stage, we use the SM bid constraint to ensure non-anticipativity, see the formulation of the SM bid in the SM problem section below. Now, the second-stage bids must be equal for all scenarios belonging to the same scenario group. See illustration in Figure 4.15.

## The SM problem

### Objective function

The objective in the SM problem is to maximize the expected total profit over the SM planning horizon $t \in T^2$, which is one day:

$$\max z^2 = \sum_{s \in S} R_s \left[ \sum_{t \in T^2} \left\{ P_{2,t,s}(\gamma_{2,t,s}^{up} - \gamma_{2,t,s}^{down}) + P_{3,t,s}(\gamma_{3,t,s}^{up} - \gamma_{3,t,s}^{down}) - \kappa_{t,s}^{up} + \kappa_{t,s}^{down} \right\} \right]. \tag{4.10}$$

This function is similar to the OM problem, except for the OM market formulations, since the OM market now is cleared and OM prices and commitments are known.

### Bid constraints

The bid format for the SM is piece-wise linear, formulated as:

$$\begin{gathered} \gamma_{2,t,s}^{up} = \frac{P_{2,t,s} - P_{2,i-1}^{bid}}{P_{2,i}^{bid} - P_{2,i-1}^{bid}} \chi_{2,i,t}^{up} + \frac{P_{2,i}^{bid} - P_{2,t,s}}{P_{2,i}^{bid} - P_{2,i-1}^{bid}} \chi_{2,i-1,t}^{up}, \\ P_{2,i-1}^{bid} < P_{2,t,s} \le P_{2,i}^{bid},\ i \in I^2,\ i \ne 1,\ t \in T^2, s \in S. \end{gathered} \tag{4.11}$$

Here, $\gamma_{2,t,s}^{up}$ is the SM commitment in period $t$ and scenario $s$, $P_{2,t,s}$ is the SM price in period $t$ and scenario $s$, $P_{2,i}^{bid}$ is the bid price for bid point $i$ and $\chi_{2,i,t}^{up}$ is the SM bid volume for bid point $i$ in period $t$. The same formulation is valid for down-regulation.

According to the bidding rules, the volume points for up-regulation must be non-decreasing with increasing price, and non-increasing for down-regulation:

$$\chi_{2,i,t}^{up} \geq \chi_{2,i-1,t}^{up}, \quad i \in I^2, i \neq 1, \ t \in T^2. \tag{4.12}$$

$$\chi_{2,i,t}^{down} \leq \chi_{2,i-1,t}^{down}, \quad i \in I^2, i \neq 1, t \in T^2. \tag{4.13}$$

The SM bid volumes $\chi_{2,i,t}^{up}$ for the highest bid point $i = I$ must be smaller than or equal to total available regulation capability $W_{u,t}^{up}$ summed over all regulation units *u* minus committed volume to OM $\gamma_{1,t}^{up}$ :

$$\chi_{2,I,t}^{up} \leq \sum_{u \in U} W_{u,t}^{up} - \gamma_{1,t}^{up}, \ t \in T^2, s \in S. \tag{4.13}$$

The same formulations are valid for down-regulation.

### Market commitment constraints

The SM problem will have market commitment constraints similar to the OM problem.

### Flexibility unit constraints

The flexibility unit constraints under the OM problem are also valid in the SM problem. In addition, we now include the time limitations by introducing binary variables. First, $\delta_{u,t,s}^{up-start}$ gets the value 1 in periods where regulation is started up in the beginning of the period. Next, $\delta_{u,t,s}^{up-end}$ gets the value 1 in periods where regulation is stopped at the end of the period. Finally, $\delta_{u,t,s}^{up-run}$ gets the value 1 in periods where regulation is ongoing, but not started or stopped in the same period. We distinguish between up- and down-regulations, so we get six different binary variable types for each regulation unit *u*, period *t* and scenario *s*: $\delta_{u,t,s}^{up-start}, \delta_{u,t,s}^{up-run}, \delta_{u,t,s}^{up-end}, \delta_{u,t,s}^{down-start}, \delta_{u,t,s}^{down-run}, \delta_{u,t,s}^{down-end}$. In the following, we present the constraints for up-regulation, but there will be identical constraints for down-regulation.

The duration of a regulation must be limited to maximum $D_u^{up-max}$ periods:

$$\sum_{j=t}^{t+D_u^{up\text{-}max}-1} \delta_{u,j,s}^{up-end} \geq \delta_{u,t,s}^{up-start}, \qquad u \in U(k),\, t \in T^2, s \in S, \tag{4.14}$$

where $j$ is a counter.

Likewise, we limit the duration to minimum $D_u^{up-min}$ periods:

$$\delta_{u,t,s}^{up-start} + \sum_{i=t}^{t+D_u^{up-min}-2} \delta_{u,i,s}^{up-end} \leq 1, \quad u \in U(k),\, t \in T^2, s \in S. \tag{4.15}$$

A minimum rest time $R_u^{up-min}$ must exist between two regulations:

$$\delta_{u,t}^{up-end} + \sum_{i=t}^{t+R_u^{up-min}} \delta_{u,i}^{up-start} \leq 1\,, \qquad u \in U(k), t \in T. \tag{4.16}$$

The number of regulations must be constrained by the maximum allowable number of regulations $B_u^{up-max}$ for the planning horizon:

$$\sum_{t \in T} \delta_{u,t,s}^{up-start} \leq B_u^{up-max}, \quad u \in U(k), s \in S. \tag{4.17}$$

The regulated volume $\chi_{u,t,s}^{up}$ can only have a non-zero value in periods where reduction starts, is running or ends. For continuous units the regulated volume must be smaller than or equal to the available regulation volume $W_{u,t,s}$:

$$\varphi_{u,t,s}^{up} \leq \delta_{u,t,s}^{up-active} W_{u,t}^{up}, \qquad u \in U^{cont}(k),\;\; t \in T^2, s \in S, \tag{4.18}$$

where $\delta_{u,t,s}^{up-active} = \min((\delta_{u,t,s}^{up-start} + \delta_{u,t,s}^{up-run} + \delta_{u,t,s}^{up-end}),1)$.

For discrete units the regulated volume must be either 0 or equal to the available regulation volume:

$$\varphi_{u,t,s}^{up} = W_{u,t}^{up} \delta_{u,t,s}^{up-active}, \qquad u \in U^{discrete}(k), t \in T^2, s \in S. \tag{4.19}$$

For shiftable regulation units $u \in U^{shift}(k)$ we in addition to the constraints above define shift time intervals $g \in G(u)$ with a start period $T_g^{start}$ and an end period $T_g^{end}$. Within each shift interval, the net sum of regulations must be 0:

$$\sum_{t=T_g^{start}}^{T_g^{end}} \left(\varphi_{u,t,s}^{up} - \varphi_{u,t,s}^{down}\right) = 0, \quad u \in U^{shift}(k), g \in G(u), s \in S. \tag{4.20}$$

Note that we did not include any of the constraints involving binary variables under the OM problem. This is a relaxation of the problem, and we selected to do so in order to reduce the calculation times.

We have not included storage units in our formulations. However, that can be done according to the formulations in Ottesen et al. (2016).

### Non-anticipativity constraints

Similar to the OM problem, the non-anticipativity constraint for the first stage in the SM problem is automatically fulfilled through the SM bid decision. The second stage constraint will now be ensured by introducing FM bids, see formulations under the FM problem below.

## The FM problem

### Objective function

The objective in the FM problem is to maximize the expected total profit over the planning horizon $t \in T^3$, which for the FM case are all hours in one day:

$$\max z^3 = \sum_{s \in S} R_s \left[ \sum_{t \in T^3} \left\{ P_{3,t,s}(\gamma_{3,t,s}^{up} - \gamma_{3,t,s}^{down}) - \kappa_{t,s}^{up} + \kappa_{t,s}^{down} \right\} \right]. \tag{4.21}$$

### Bid constraints

Since the FM bid format is step-wise, similar to the OM bid, the bid formulations will be equal. However, the FM commitment $\gamma_{3,t,s}^{up}$ is also conditional on the regulation direction in the market, which can be derived from the difference in prices between the SM and FM. The market is up-regulated in a period if $P_{3,t} > P_{2,t}$, down-regulated if $P_{3,t} < P_{2,t}$ and unregulated if $P_{3,t} = P_{2,t}$. The bid constraint then can be formulated as:

$$\gamma_{3,t,s}^{up} = \begin{cases} \chi_{3,i,t}^{up}, \ i \in I^3, \ t \in T^3, s \in S \ \ if \ P_{3,i}^{bid-up} < P_{3,t,s} \leq P_{3,i+1}^{bid-up} \ and \ P_{2,t,s} < P_{3,t,s} \\ 0, \quad \ i \in I^3, \ t \in T^3, s \in S \ \ if \ P_{3,t,s} \leq P_{2,t,s} \end{cases} \tag{4.22}$$

$$\gamma_{3,t,s}^{down} = \begin{cases} \chi_{3,i,t}^{down}, \ i \in I^3, \ t \in T^3, s \in S \ \ if \ P_{3,i}^{bid-up} < P_{3,t,s} \leq P_{3,i+1}^{bid-down} \ and \ P_{2,t,s} > P_{3,t,s} \\ 0, \quad \ i \in I^3, \ t \in T^3, s \in S \ \ if \ P_{3,t,s} \leq P_{2,t,s} \end{cases} \tag{4.23}$$

According to the bidding rules, the volume points for up-regulation must be non-decreasing with increasing price, and non-increasing for down-regulation:

$$\chi_{3,i,t}^{up} \geq \chi_{3,i-1,t}^{up}, \quad i \in I^m, i \neq 1, t \in T^3. \tag{4.24}$$

$$\chi_{3,i,t}^{down} \leq \chi_{3,i-1,t}^{down}, \quad i \in I^m, i \neq 1, t \in T^3. \tag{4.25}$$

Volume bid to the FM for up-regulation $\chi_{3,i,t}^{up}$ for the last bid point $i = I^3$ must be greater than or equal to committed volume in the OM:

$$\chi_{3,I,t}^{up} \geq \gamma_{1,t}^{up}, \quad t \in T^3. \tag{4.26}$$

### Market commitment constraints

The FM problem will have market commitment constraints similar to the OM and SM problems.

### Flexibility unit constraints

The FM problem we will have the same flexibility unit constraints as the SM problem.

### Non-anticipativity constraints

Since the FM problem is in only two stages, we only need non-anticipativity constraints for the first stage, which are automatically ensured by the FM bid constraints.

## The scheduling problem

The objective in the scheduling problem is to maximize the total profit over the planning horizon $t \in T^4$. Now, all trading decisions are made and all commitments are known. The only decision to make is schedules for all the flexibility units so that the difference between down-regulation reduced cost and up-regulation added cost is minimized.

$$\max z^4 = -\kappa_{t,s}^{up} + \kappa_{t,s}^{down}. \tag{4.27}$$

Since no bid decisions are to be made, we will have no bid constraints. Further, we do not need any non-anticipativity constraints, since all parameters are known with certainty and the problem is deterministic. However, we need the market commitment and flexibility unit constraints. These will be similar to the formulations under the OM and SM problems, but without the notion of scenarios.

# 4.4. Case study

## Portfolio description

We perform a case study in close cooperation with Statkraft[21] and four Norwegian industrial companies. We simulate that Statkraft acts as the flexibility aggregator and that the industrial companies are flexibility vendors. The flexibility capabilities including constraints have been worked out in close cooperation with the staff at the industrial facilities. The flexibility portfolio is illustrated in Figure 4.4.

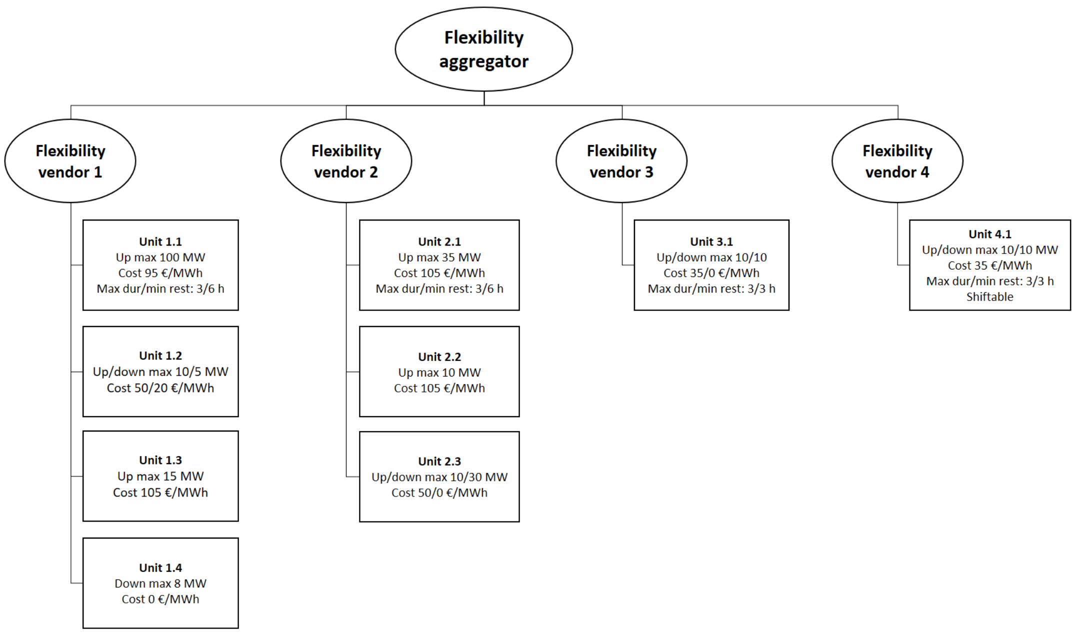


*Figure 4.4. Flexibility portfolio*

In total, the portfolio consists of 9 regulation units. Each unit represents a production line or a group of steam generating appliances. Five units can only regulate in one direction (up or down), while the rest can regulate in both directions. Total capability for up-regulation is maximum 200 MW, while the corresponding value for down-regulation is 63 MW. Up-regulation costs are 35, 50, 95 and 105 €/MW, while down-regulation reduced costs are 20 and

[21] www.statkraft.com

0 €/MW. Figure 4.5 shows the aggregated volumes for these costs. Note that the figures show maximum values and do not reflect unavailability or time limitations.

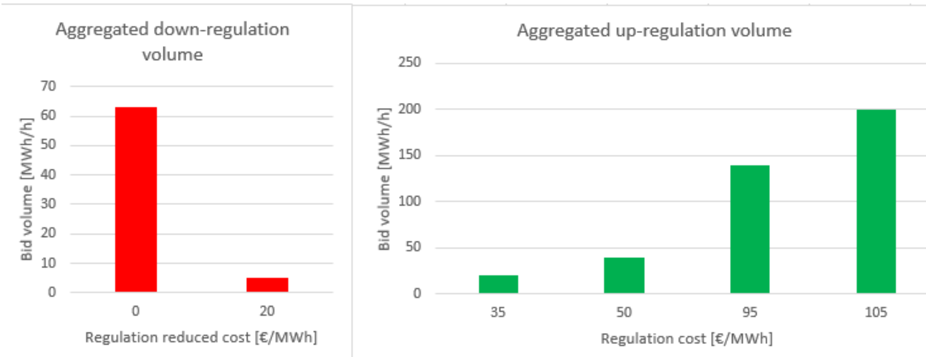


*Figure 4.5. Aggregated volumes for down- and up-regulation*

While units 1.2, 1.3, 1.4, 2.2 and 2.3 can perform regulations without any inter-period constraints, units 1.1, 2.1, 3.1 and 4.1 have several constraints: All units have a maximum regulation duration of 3 hours. Further, unit 1.1 and 2.1 have minimum 6 hours' rest time, while unit 3.1 and 4.1 have 3 hours. Finally, unit 4.1 has a volume constraint, where the sum of up-regulation and down-regulation must equal 0 over a day.

Available flexibility for a typical day will be as presented in Figure 4.4 for each of the hours, except for unit 1.4, which has only 7 MW available for down-regulation from hour 7 to 10, and for unit 2.3, which has possibility to regulate down 30 MW the first half day and up 10 the rest of the day. Moreover, unit 1.1 and 2.1 will be stopped once a month. For these days the capability will be 0 between hour 7 and 18.

## Market conditions

To represent the OM, SM and FM, we use prices from Statnett's Tertiary reserves options market ("RKOM uke"), Nord Pool's Elspot day-ahead market and Statnett's Tertiary reserves market ("RK"), respectively. There is one RKOM price per week, and this price is valid for each day from hour 6 to 24. In RKOM resources for up-regulation are reserved for later use in RK. For Elspot and RK there is one price for each hour. The simulations are run on data for the 8 first weeks in 2016, namely from 04.01.2016 to 28.02.2016. Real prices for the three markets are shown in Figure 4.6 and Figure 4.7.

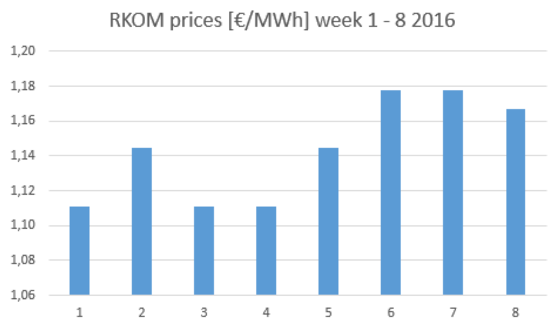


*Figure 4.6. Real RKOM prices for the first 8 weeks of 2016*

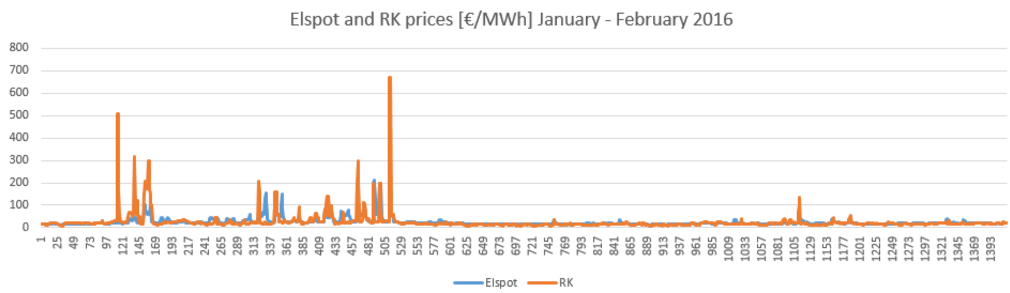


*Figure 4.7. Real Elspot and RK prices for January and February 2016*

Note in particular the extraordinarily spiky price pattern for Elspot and RK for January, and the much more dampened situation in February.

## Process overview

To perform our analyses, we go through the steps described in section 4.2, illustrated in Figure 4.8, where each rectangle with ordinary corners represents a process and a model, while the rectangles with snipped corners represent input or output files.

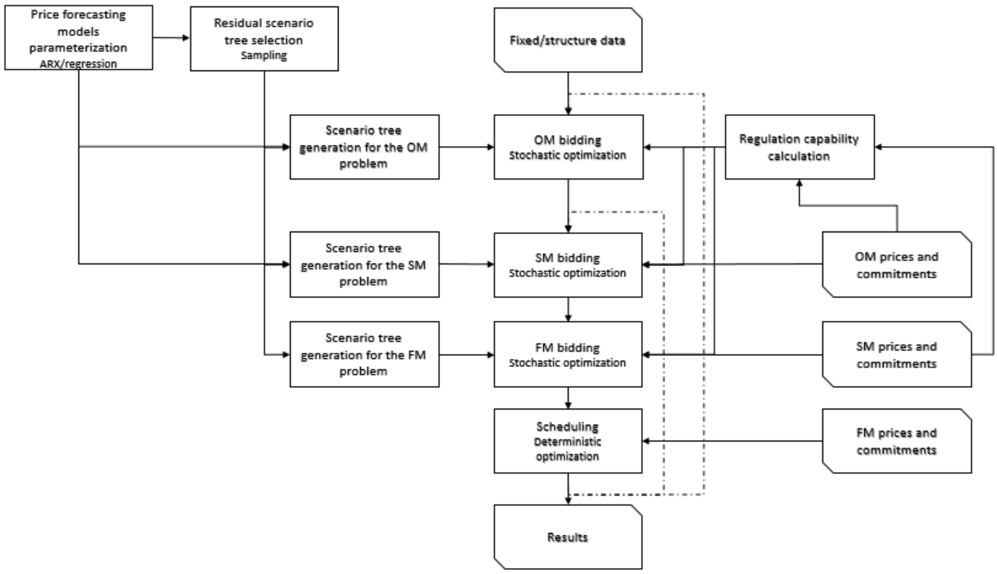


*Figure 4.8. Overview of bidding and scheduling simulation process*

## Results and analysis for one specific day

In this section we analyze one day in detail. We select 15.01.2016, which is Friday in week 2. The OM price for this week cleared at 1.14 €/MWh and is valid for all hours between 6 and 24. An overview of realized prices in SM and FM for the day is shown in Figure 4.9.

The SM prices vary between 23 and 150 €/MWh with a morning and evening peak. There is up-regulation in FM to high prices (up to 160 €/MWh) from hour 7 to 10, else down-regulation from hour 1 to 3 (to prices below 20 €/MWh) and 14 to 20 (to prices above 20 €/MWh). This means that all up-regulation units are candidates for regulation in the SM and FM, and that unit 1.2 is candidate for down-regulation in the FM. Recall that the prices are not known at the time we make our decisions.

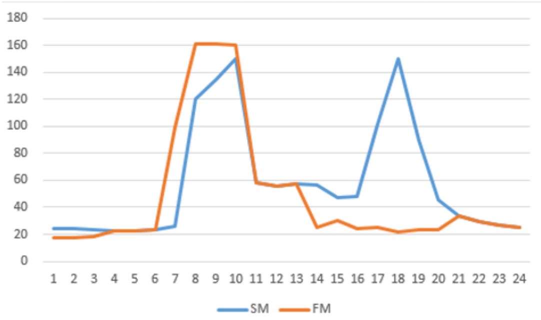


*Figure 4.9. Real prices for the SM and FM for 15.01.2016*

Before making decisions for the specific day, we must decide the OM bid for the whole week. Then we need price scenarios for the OM, SM and FM, which we generate according to the description in Appendix 4.B. The OM decision is a trade-off between expected profits from the OM and FM on one side and from the SM on the other side. The resulting bids are shown in Figure 4.18. Remember that these bids are valid for hour 6 to 24 all days for week 2, including our focal day, 15.01.2016. Since the OM price for week 2 realized at 1.14 €/MWh, our commitment is 170 MWh/h.

For the SM decision we need price scenarios for the SM and FM. The resulting SM bids are shown in Figure 4.19. The bids for the FM problem are presented in Figure 4.20.

When the FM prices are published, the final schedule to be implemented can be calculated in the scheduling problem. The left part of Figure 4.10 shows the commitments to each market, the right part shows the net profit, also split down to each revenue and cost element, while Figure 4.11 shows the schedules for each flexibility unit.

For the hours 6 to 24, the OM commitment is 170 MWh/h, which means that total available volume for SM is 20 MWh/h from 6 – 12 and 30 from 13 – 24. We see that we sell up-regulation in the highest priced hours in SM (8-10 and 17-19) plus some other hours. In FM we first get down-regulation for hours 1 – 3 (where prices are below 20) and then up-regulation for 8 – 10. The optimal utilization of each regulation unit is presented in Figure 4.11. Note that all constraints are fulfilled: Units 1.1, 2.1, 3.1 and 4.1 run for maximum three hours, unit 1.1 has six hours' rest-time between the regulations, while unit 3.1 has three hours'. Unit 4.1 has 5 MWh down-regulation in hour 1 and 3 and 10 MWh up-regulation in hour 10, which gives net 0.

In total, these decisions give a net profit equal to 45 k€ for the day, where the largest amount of revenues come from FM.

| Period | Option up | Spot up | Spot down | Flex up | Flex down |
|---|---|---|---|---|---|
| 1 | 0,0 | 0,0 | 0,0 | 0,0 | 5,0 |
| 2 | 0,0 | 0,0 | 0,0 | 0,0 | 5,0 |
| 3 | 0,0 | 0,0 | 0,0 | 0,0 | 5,0 |
| 4 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 5 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 6 | 170,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 7 | 170,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 8 | 170,0 | 20,0 | 0,0 | 160,0 | 0,0 |
| 9 | 170,0 | 20,0 | 0,0 | 160,0 | 0,0 |
| 10 | 170,0 | 20,0 | 0,0 | 160,0 | 0,0 |
| 11 | 170,0 | 3,3 | 0,0 | 0,0 | 0,0 |
| 12 | 170,0 | 10,0 | 0,0 | 0,0 | 0,0 |
| 13 | 170,0 | 30,0 | 0,0 | 0,0 | 0,0 |
| 14 | 170,0 | 30,0 | 0,0 | 0,0 | 0,0 |
| 15 | 170,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 16 | 170,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 17 | 170,0 | 30,0 | 0,0 | 0,0 | 0,0 |
| 18 | 170,0 | 30,0 | 0,0 | 0,0 | 0,0 |
| 19 | 170,0 | 30,0 | 0,0 | 0,0 | 0,0 |
| 20 | 170,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 21 | 170,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 22 | 170,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 23 | 170,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 24 | 170,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| | 3230,0 | 223,3 | 0,0 | 480,0 | 15,0 |

| | | |
|---|---|---|
| OM up revenue | 3 682 | € |
| SM up revenue | 22 510 | € |
| FM up revenue | 77 005 | € |
| Regulation up cost | 57 963 | € |
| SM down cost | 0 | € |
| FM down cost | 266 | € |
| Regulation down reduced cost | 100 | € |
| | | |
| | | |
| Net profit up: | 45 234 | € |
| Net profit down: | -166 | € |
| Net profit w/o option | 41 385 | |
| | | |
| **Net profit total:** | **45 068** | **€** |

*Figure 4.10. Market commitments and economic figures for 15.01.2016*

| | Up-regulation | | | | | | | | Down-regulation | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1.1 | 1.2 | 1.3 | 2.1 | 2.2 | 2.3 | 3.1 | 4.1 | 1.2 | 1.4 | 2.3 | 3.1 | 4.1 |
| 1 | | | | | | | | | | | | | 5.5 |
| 2 | | | | | | | | | 5.5 | | | | |
| 3 | | | | | | | | | | | | | 5.5 |
| 4 | | | | | | | | | | | | | |
| 5 | | | | | | | | | | | | | |
| 6 | | | | | | | | | | | | | |
| 7 | | | | | | | | | | | | | |
| 8 | 100.0 | 10.0 | 15.0 | 35.0 | 10.0 | | 10.0 | | | | | | |
| 9 | 100.0 | 10.0 | 15.0 | 35.0 | 10.0 | | 10.0 | | | | | | |
| 10 | 100.0 | 10.0 | 15.0 | 35.0 | 10.0 | | | 10.0 | | | | | |
| 11 | | 3.3 | | | | | | | | | | | |
| 12 | | 10.0 | | | | | | | | | | | |
| 13 | | 10.0 | | | | 10.0 | 10.0 | | | | | | |
| 14 | | 10.0 | | | | 10.0 | 10.0 | | | | | | |
| 15 | | | | | | | | | | | | | |
| 16 | | | | | | | | | | | | | |
| 17 | 10.0 | 10.0 | | | | 10.0 | | | | | | | |
| 18 | | 10.0 | | | | 10.0 | 10.0 | | | | | | |
| 19 | | 10.0 | | | | 10.0 | 10.0 | | | | | | |
| 20 | | | | | | | | | | | | | |
| 21 | | | | | | | | | | | | | |
| 22 | | | | | | | | | | | | | |
| 23 | | | | | | | | | | | | | |
| 24 | | | | | | | | | | | | | |

*Figure 4.11. Unit schedules for 15.01.2016*

## Results and analysis for 8 weeks

Figure 4.12 sums up the results from simulations over 8 weeks. The total net profit is 819 k€, which can be interpreted as the value of flexibility. Note that January contributes with 86 % of the profit, due to the higher price levels in SM and FM compared to February.

| | Grand total | Sum January | Sum February |
|---|---|---|---|
| OM up revenue | 168 159 | 70 803 | 97 356 |
| SM up revenue | 179 695 | 179 044 | 651 |
| FM up revenue | 945 140 | 916 438 | 28 703 |
| Regulation up cost | 488 372 | 468 892 | 19 481 |
| SM down cost | 23 445 | 7 157 | 16 288 |
| FM down cost | 36 462 | 15 718 | 20 744 |
| Regulation down reduced cost | 74 194 | 26 554 | 47 640 |
| | | | |
| | | | |
| Net profit up: | 804 622 | 697 393 | 107 229 |
| Net profit down: | 14 287 | 3 679 | 10 607 |
| Net profit w/o option | 636 463 | 626 590 | 9 873 |
| | | | |
| **Net profit total:** | 818 908 | 701 072 | 117 836 |

*Figure 4.12. Results for 04.01.2016 to 28.02.2016*

Profits from down-regulation are almost negligible compared to up-regulation (14 versus 805 k€). One reason for this is that the portfolio has larger amounts of up-regulation capabilities, another is that most of the down-regulation is profitable only for negative prices. In addition, as we saw in January, the market prices may get extremely high, but rarely extremely negative.

For the up-regulation, 73 % of the revenues stem from FM, while 13 and 14 % stem from OM and SM, respectively. The markets that are specifically designed for flexibility, OM and FM, together contributes with 87 % of the revenues.

For February, OM and SM contributes with 99 % of the up-regulation revenues, but here OM has the largest impact (76 %). In addition, with the low prices in February, net profit for down-regulation is almost three times larger than for January.

To calculate the theoretical upper bound of net total profit and to analyze under what conditions our models are not able to realize the full potential, we repeat the simulations for the 8 weeks' period, but this time we assume that we have perfect information, meaning that we know exactly what the prices will be in the future. Instead of making price scenarios, we enter realized prices as input to our models. This is of course unrealistic in real life, but we perform this in order to analyze the difference between the solutions from the stochastic program (SP) and from calculations with perfect information (PI). The overall results from PI are presented in Figure 4.13.

| | Grand total | Sum January | Sum February |
|---|---|---|---|
| OM up revenue | 190 383 | 93 027 | 97 356 |
| SM up revenue | 118 893 | 117 791 | 1 102 |
| FM up revenue | 1 332 090 | 1 288 640 | 43 450 |
| Regulation up cost | 570 249 | 537 874 | 32 375 |
| SM down cost | 24 726 | 5 946 | 18 781 |
| FM down cost | 48 190 | 21 352 | 26 838 |
| Regulation down reduced cost | 90 600 | 31 700 | 58 900 |
| | | | |
| | | | |
| | | | |
| Net profit up: | 1 071 118 | 961 585 | 109 533 |
| Net profit down: | 17 684 | 4 402 | 13 282 |
| Net profit w/o option | 880 735 | 868 558 | 12 177 |
| | | | |
| **Net profit total:** | **1 088 802** | **965 987** | **122 814** |

*Figure 4.13. Results for 04.01.2016 to 28.02.2016 based on perfect information*

Net total profits are now 1 089 k€ or 33 % higher than results from SP. Most of the difference comes in January.

There are multiple reasons why the solutions differ between SP and PI. First, SP in general chooses strategies that are more robust in meeting different outcomes of the stochastic variables (market prices). In our case this happens for example for the OM decisions, where SP in general decides a lower OM volume. By doing so, the aggregator is more flexible in meeting potential high SM prices. This is in line with stochastic programming theory, see for instance Kall & Wallace (1994).

Further, PI is able to generate larger profits for the volume constrained unit (4.1), since it knows with certainty what all prices are going to be. In SP, this unit is less utilized since we might need to regulate it to high costs to ensure feasible solutions for every scenario.

However, five days contribute with 84 % of the difference in profits between PI and SP. All these are extreme days, with very high prices, in particular in the FM, that are difficult to forecast and to cover in the price scenarios. In Figure 4.12 and 4.13 we see that SP allocates more to the SM compared to PI. When the extreme prices occur in the FM, the SP solutions sometimes have allocated volumes to SM and the aggregator can not put maximum volume to the hours with extreme prices in FM. Another reason is that SP in the FM bid has allocated large volumes to FM, but not to the hours where the extreme prices really come. Note that we in our modelling have simplified the FM process, by assuming that bids are sent once a day and that all 24 FM prices are revealed simultaneously. In real life in the tertiary reserves market, this is not the case. The prices are revealed after each hour, and the market participants can change their bids throughout the day. Hence, in a more realistic setting, the problems described above could have been reduced and the profits in SP would have been higher.

This shows that proper price forecasting and scenario generation models are very important. Anyway, no matter how advanced price forecasting models we have, some of the price events in January would be impossible to forecast.

For the scenario generation method, it is particularly important to have a good spread of the scenario fan. Ideally, in the total set of scenarios there should exist one price between each bid price point for each hour. Without this requirement fulfilled, the model sees no probability that the price will realize between these points, and it will be indifferent of what volume to bid here. This might be a problem if the price realizes between these points.

This article focuses on an entity that aggregates flexibility and sells it in markets. Basically, the aggregator performs services on behalf of each flexibility vendor, aiming at lowering the barriers in accessing the market and reducing the transaction costs (Eurelectric, 2014). However, it is interesting to analyse if the aggregator role has any additional value added impacts on the value chain. To do so, we have performed the simulations for each flexibility vendor separately. The summed results are presented in Figure 4.14.

Total profits are now 793 k€, which is 26 k€ or 3 % lower than the total profits in the aggregated case (Figure 4.12). Hence, the value of aggregation is 26 k€. A closer analysis of the results shows that there are different reasons for the added value: First, a larger portfolio of flexibility units provides more robustness to make feasible solutions, and hence, larger volumes can be bid into the markets. An example to illustrate: Assume that unit 2.1 (35 MWh/h) and unit 1.3 (15 MWh/h) are planned out of operation during some hours of the week (but not simultaneously). The total regulating capability will be 50 MWh/h when both run, 35 MWh/h when only 1.2 runs and 15 MWh/h when 1.3 runs. In the disaggregated case none of these units can be bid into OM. In the aggregated case, however, 15 MWh/h can still be bid to OM, since 15 can be provided to hours where both run, 2.1 runs and 1.3 runs. Aggregation releases 15 MWh/h to OM in this example.

| Total | | | |
|---|---|---|---|
| | Grand total | Sum January | Sum February |
| OM up revenue | 157 824 | 60 468 | 97 356 |
| SM up revenue | 192 146 | 191 370 | 776 |
| FM up revenue | 944 358 | 916 997 | 27 361 |
| Regulation up cost | 516 655 | 497 407 | 19 248 |
| SM down cost | 17 360 | 5 152 | 12 208 |
| FM down cost | 39 877 | 17 137 | 22 740 |
| Regulation down reduced cost | 72 071 | 26 668 | 45 403 |
| | | | |
| | | | |
| Net profit up: | 777 674 | 671 429 | 106 245 |
| Net profit down: | 14 834 | 4 379 | 10 455 |
| Net profit w/o option | 619 849 | 610 960 | 8 889 |
| | | | |
| **Net profit total:** | 792 508 | 675 808 | 116 700 |
| | | | |
| **Results from aggregated solutions** | 818 908 | 701 072 | 117 836 |
| | | | |
| **Value of aggregation** | 26 400 | 25 264 | 1 136 |

*Figure 4.14. Results without aggregation*

A larger portfolio also gives increased robustness to utilize flexibility units with constraints. Take unit 4.1 as an example. This unit is volume constrained and must, if it has been regulated up at the beginning of the day, be regulated down at the end of the day. If the market is not regulated down, we must regulate up at another unit simultaneously with down-regulation of 4.1. Without aggregation, there are no other candidates to regulate, since vendor 4 only has this unit.

## Discussion

The multi-market bidding problem for a flexibility aggregator is a complex task. In order to formulate the problem mathematically and to perform the case study, we have made some simplifications and assumptions.

We assume that the portfolio can be bid aggregated into all markets. Whether this assumption holds, depends on the specific market design and the geographical location for each flexibility vendor. If the flexibility vendors can not be bid aggregated, for instance if they belong to different zones or the FM must be bid down to node level, the value of aggregation will decrease. Further, we have disregarded costs related to grid-tariffs. In cases with dynamic grid prices, for instance with charges related to maximum power feed-in or outtake or to different grid prices in different periods (time-of-use), the grid tariff should also be included in the decision model (Ottesen & Tomasgard, 2015)).

We have defined our problem so that the aggregator plans his operations into balance and fulfils the commitments perfectly. In a real life setting, there will be an imbalance market or some kind of penalization for not meeting obligations. We leave this to future research, but mention that our models managed to find feasible solutions in all cases. Inclusion of the possibility to have imbalances might on one hand introduce additional costs, but on the other hand make it easier to find feasible solutions. We have also assumed that the regulation capabilities are known with certainty, which in a real situation would probably not hold. Further, we have assumed that there is no inter-relation between days regarding regulation capabilities. Then, decisions for the SM and FM can be done for each day separately, without considering later days. In situations where this assumption does not hold, the decision problem will be more complex.

In this paper, we collapse the number of stages down to maximum three and establish a new model for each bid decision to make. This is in contrast to the approach in for instance Boomsma et al. (2014), who solve all problems in one, large multistage program. By applying their approach to our problem, we would for instance in the OM problem have SM prices being realized in seven stages for a week, and where each realization is conditional on realizations in all the earlier stages. Due to our disregard, one could expect a loss in profit, but the analysis with perfect information indicates that this loss is limited. The reason is that different realizations in late stages and their correlations will have little impact to the first stage decision. Further, we also want to pinpoint that making realistic scenarios for late stages is a difficult task. Finally, a strength with our method is that it handles situations where market prices realize differently from the scenarios, which normally will be the case.

The case study is deliberately run for the two first months of 2016, since we then both cover extreme situations with high and volatile prices including many periods with up-regulation and periods with flat and low prices including a lot of down-regulation. To no surprise, we see that the profit potential is largest in situations with high prices and up-regulation. It should be mentioned that January 2016 is peak demand month in the Norwegian electricity market, and hence, the profit figures should be used with care.

The numeric results from the case study indicate that proper models for price forecasting and scenario generation are very important in volatile situations. Implementation of our models in a real life setting would require more advanced forecasting and scenario generation methods which improve how 1) price changes are captured and 2) the scenario fan is spread out. Further, it should be evaluated if the number of price scenarios should be higher. We have seen some days with indifference problems. However, even with our simplifications and assumptions, we have been able to harvest a large proportion of the potential profit.

We have assumed that the aggregator is risk neutral, with no limitations on the bid volumes. For a real aggregator, we assume that limitations might be put on bid volumes (Deng, Shen, & Sun, 2006; Faria & Fleten, 2009), for example on the OM bid. Another approach could be to introduce the aggregator's preferences in the weight of participation in the different markets as outlined in Triki et al. (2005). However, we leave the risk profile topic to later research.

# 4.5. Conclusion and future research

In this paper we propose decision-support models to handle the bidding and scheduling problems for aggregators that manage a portfolio of demand side flexibility by trading in multiple, sequential electricity markets. We have illustrated the application of the models in a case study where we have established a hypothetical portfolio, yet based on real flexibility units. Real data and rules are used from three current Norwegian electricity markets to simulate over a two-month period: January and February 2016. The study shows that our models ensure that bids and schedules are feasible. Further, we have calculated the value of flexibility and analysed how the different markets generate profits and discussed how this is influenced by price levels, price variations and directions of regulation. The total net profit is 819 k€, where 98 % comes from up-regulation and 86 % comes from January, where the prices were very high due to cold temperatures.

To analyse how well the models perform, we have compared with an analysis based on perfect information. We find that the value of the flexibility is 30 % higher with perfect information and that the reason for the loss is two-fold: 1) The stochastic approach chooses strategies that are more flexible to possible different outcomes of the market prices and 2) due to the spiky price situation in January which was very difficult to predict. This also shows the importance of proper price forecasting models and scenario generation methods.

Finally, we have analysed how the aggregator adds value to the portfolio by comparing to a situation where each flexibility vendor participates in the markets separately. We find that the value is 3 % due to increased ability to commit volumes to the markets and to provide feasible scheduling solutions for the flexibility units.

In our work we disregard imbalances by forcing the schedules to match market commitments and fulfil the flexibility units' constraints perfectly. Further, we assume that available flexibility is known with certainty and do not include potential impact from grid tariffs. Finally, we have simplified the FM by assuming that bid is submitted only once a day with no possibility to change as prices are revealed.

We have only looked at the portfolio as a whole without analysing how the profits should be distributed between the flexibility vendors. In a real life setting, this will of course be an important question to answer. Furthermore, to analyse the profitability, the investment cost for equipment both at the flexibility vendor side and at the aggregator side, should be quantified.

## Acknowledgements

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# 4.6. Appendices

## Appendix 4.A. Sets, parameters and variables

| | |
|---|---|
| $M$ | Set of markets, indexed by *m*, where 1 = options market, 2 = spot market and 3 = flexibility market. |
| $T^m \subset T$ | Subset of time periods where market *m* is valid. |
| $K$ | Set of flexibility vendors, indexed by *k*. |
| $U$ | Set of regulation units, indexed by *u*. |
| $U^{cont} \subset U$ | Subset of regulation units of type continuous. |
| $U^{discrete} \subset U$ | Subset of regulation units of type discrete. |
| $U^{shift} \subset U$ | Subset of regulation units of type shiftable. |
| $G$ | Set of possible load shift time intervals, indexed by *g*. |
| $L$ | Set of storage units, indexed by *l*. |
| $S$ | Set of scenarios, indexed by *s*. |
| $I^m$ | Set of bid points valid for market m, indexed by *i*. |

| | |
|---|---|
| $R_s$ | Probability for scenario *s*. |
| $P_{1,t,s}^{up}$ | Market price for reservation of up-regulation in the OM market in period *t* and scenario *s* [€/MWh]. |
| $P_{1,t,s}^{down}$ | Market price for reservation of down-regulation in the OM market in period *t* and scenario *s* [€/MWh]. |
| $P_{m,t,s}$ | Market clearing price in market *m* in period *t* and scenario *s* [€/MWh]. These parameters are valid for the SM and FM. |
| $P_u^{up}$ | Internal cost for regulating up at regulating unit *u* in period *t* and scenario *s* [€/MWh]. |
| $P_u^{down}$ | Internal utility (negative cost) for regulating down at regulating unit *u* in period *t* and scenario *s* [€/MWh]. |
| $W_{u,t}^{up}$ | Volume available for regulation up at regulating unit *u* and period *t* [MW]. |
| $W_{u,t}^{down}$ | Volume available for regulation down at regulating unit *u* and period *t* [MW]. |
| $D_u^{up-max}$ | Maximum duration of a regulation up at regulating unit *u* [# of periods]. |
| $D_u^{down-max}$ | Maximum duration of a regulation down at regulating unit *u* [# of periods]. |
| $D_u^{up-min}$ | Minimum duration of a regulation up at regulating unit *u* [# of periods]. |
| $D_u^{down-min}$ | Minimum duration of a regulation down at regulating unit *u* [# of periods]. |

| | |
|---|---|
| $R_u^{up-min}$ | Minimum rest time between two regulations up at regulating unit $u$ [# of periods]. |
| $R_u^{down-min}$ | Minimum rest time between two regulations down at regulating unit $u$ [# of periods]. |
| $B_u^{up-max}$ | Maximum number of regulations up at regulating unit $u$. |
| $B_u^{down-max}$ | Maximum number of regulations down at regulating unit $u$. |
| $T_g^{start}$ | Earliest possible start period for load shift time interval $g$. |
| $T_g^{end}$ | Latest possible end period for load shift time interval $g$. |

| | |
|---|---|
| $\chi_{m,b,t}^{up}$ | Bid volume for up-regulation in market $m$ at bid point $b$ and period $t$ [MW]. |
| $\chi_{m,b,t}^{down}$ | Bid volume for down-regulation in market $m$ at bid point $b$ and period $t$ [MW]. |
| $\gamma_{m,t,s}^{up}$ | Committed volume for up-regulation in market $m$ in period $t$ and scenario $s$ [MW]. |
| $\gamma_{m,t,s}^{down}$ | Committed volume for down-regulation in market $m$ in period $t$ and scenario $s$ [MW]. |
| $\kappa_{t,s}^{up}$ | Internal cost for regulating up in period $t$ and scenario $s$ [€]. |
| $\kappa_{t,s}^{down}$ | Internal utility (negative cost) for regulating down in period $t$ and scenario $s$ [€]. |
| $\varphi_{u,t,s}^{up}$ | Power regulated up at regulating unit $u$ in period $t$ and scenario $s$ [MW]. |
| $\varphi_{u,t,s}^{down}$ | Power regulated down at regulating unit $u$ in period $t$ and scenario $s$ [MW]. |
| $\chi_{m,b,t}^{up}$ | Volume bid for regulation up to market $m$ at bid point $b$ in period $t$ [MW]. |
| $\chi_{m,b,t}^{down}$ | Volume bid for regulation down to market $m$ at bid point $b$ in period $t$ [MW]. |
| $\delta_{u,t,s}^{up-start}$ | Binary variable = 1 if regulation up starts in the beginning of period $t$ for regulating unit $u$ in scenario $s$. |
| $\delta_{u,t,s}^{up-run}$ | Binary variable = 1 if regulation up runs for regulating unit $u$ in period $t$ and scenario $s$. |
| $\delta_{u,t,s}^{up-end}$ | Binary variable = 1 if regulation up ends in the end of period $t$ for regulating unit $u$ in scenario $s$. |
| $\delta_{u,t,s}^{down-start}$ | Binary variable = 1 if regulation down starts in the beginning of period $t$ for regulating unit $u$ in scenario $s$. |
| $\delta_{u,t,s}^{down-run}$ | Binary variable = 1 if regulation down runs for regulating unit $u$ in period $t$ and scenario $s$. |
| $\delta_{u,t,s}^{down-end}$ | Binary variable = 1 if regulation down ends in the end of period $t$ for regulating unit $u$ in scenario $s$. |

## Appendix 4.B. Forecasting and scenario generation

Our case study contains three types of uncertain parameters: OM prices, SM prices and FM prices. We make scenario trees for these uncertain parameters, basically following the same approach as in Ottesen et al. (2016): First, we make a forecasting model and generate price forecast $P_{m,t}^{forecast}$ for the actual market and time periods. Next, we sample residuals $\varepsilon_{m,t}$ and add to the forecast to generate scenarios.

$$P_{m,t,s} = P_{m,t}^{forecast} + \varepsilon_{m,t}, \quad m \in M, t \in T, s \in S. \tag{4.29}$$

OM price forecasting: We use data from RKOM for 2009 – 2015 to calibrate the model and explain the price for one week by the price one week, two weeks and one year back.

$$p_u^{OM} = \mu + \varphi_1 p_{u-1}^{OM} + \varphi_2 p_{u-2}^{OM} + \varphi_{52} p_{u-52}^{OM} + \varepsilon_u. \tag{4.30}$$

SM price forecasting: We parameterize the model on data for 2013 to 2015. We need two types of SM price forecasts: one for the OM problem and one for the SM problem. A SM price forecast for the OM problem must be for a whole week (168 prices) and must be based on information available at the time when we make the forecast. We explain the price for an hour by SM price one week back, one year back, the OM price one week back and the temperature forecast. To smooth out extreme values, we model the natural logarithm of the price.

$$\ln p_t^{SM} = \mu + \varphi_1 \ln p_{t-168}^{SM} + \varphi_2 \ln p_{t-8760}^{SM} + \varphi_3 p_{t-168}^{OM} + \varphi_4 \psi_t^{temp} + \varepsilon_t. \tag{4.31}$$

The SM price forecast for the SM problem will be for 24 hours and is explained by SM price one day, two days and one week back, maximum price one day back, forecasted load published by Nord Pool Spot plus dummy variables for Mondays, Saturdays and Sundays.

$$\begin{aligned} \ln p_t^{SM} = {} & \mu + \varphi_1 \ln p_{t-24}^{SM} + \varphi_2 \ln p_{t-48}^{SM} + \varphi_3 \ln p_{t-168}^{SM} + \\ & \varphi_4 \ln mp_t^{SM} + \psi \ln f_t + d_1 D_{Mon} + d_2 D_{Sat} + d_3 D_{Sun} + \varepsilon_t. \end{aligned} \tag{4.32}$$

For FM prices we have chosen a different approach without making a price forecast. In our case study the FM prices are directly dependent on the SM prices, since the SM price is the starting point for the FM price. In addition, activations in the FM are performed only when incidents occur that are not accounted for in SM, for instance that weather conditions realize differently from the weather forecast or grid components are disconnected due to failures. Such events are difficult to predict due to the randomly characteristics (exogenously driven stochastic process), so we have chosen not to make any price forecasting model for FM.

To generate OM scenarios, we sample residuals from the forecasting model and use property matching (for details, see appendix B in Ottesen et al. (2016)). SM scenarios are also based on residuals sampling from the forecasting models. Due to the strong autocorrelation in the residuals, we sample complete series, 168 values for the OM problem and 24 for the SM problem. However, for the SM and FM price scenarios we have chosen a slightly different method with two objectives: 1) The scenario tree should have values that on expectation are as close as possible to the forecasted value. 2) The scenario tree should span out the scenario fan to limit the indifference problem. The reason behind changing the method is that the first one often do not span out the scenario fan properly. To further reduce the indifference problem, we also add two extreme scenarios related to the lowest and highest realized prices in the calibration period. This is done only to the first stage problem (OM prices for the OM problem, SM prices for the SM problem and FM prices for the FM problem).

FM scenarios are generated the same way as SM scenarios, except that the samples are not based on residuals, but from realized differences between SM and FM prices directly. Note that for the SM problem, FM price scenarios are generated by adding samples to the SM scenario, while for the FM problem, FM scenarios are generated by adding samples to the SM price, which now is known with certainty.

For the OM and SM problem we have a three-stage scenario tree with 34 scenarios. We sample 8 scenarios for the realization of first stage parameters. Next, we sample 32 scenarios for the realization of second stage parameters. The 32 second stage samples are randomly combined with the 8 first stage samples. Finally, we add extreme low and high scenarios for first stage parameters.

These principles result in scenarios illustrated with some examples in the figures below. Figure 4.16 shows price scenarios to the OM problem for week 1 (04.01.2016 – 10.01.2016), while Figure 4.17 shows scenarios to the SM (two first rows) and FM (third row) problems for 04.01.2016.

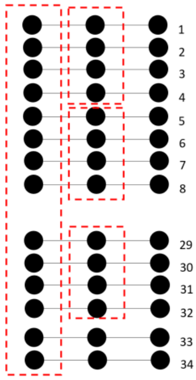


*Figure 4.15. Scenario tree structure for the OM and SM problems*


*Figure 4.16. Examples of scenarios to the OM problem*

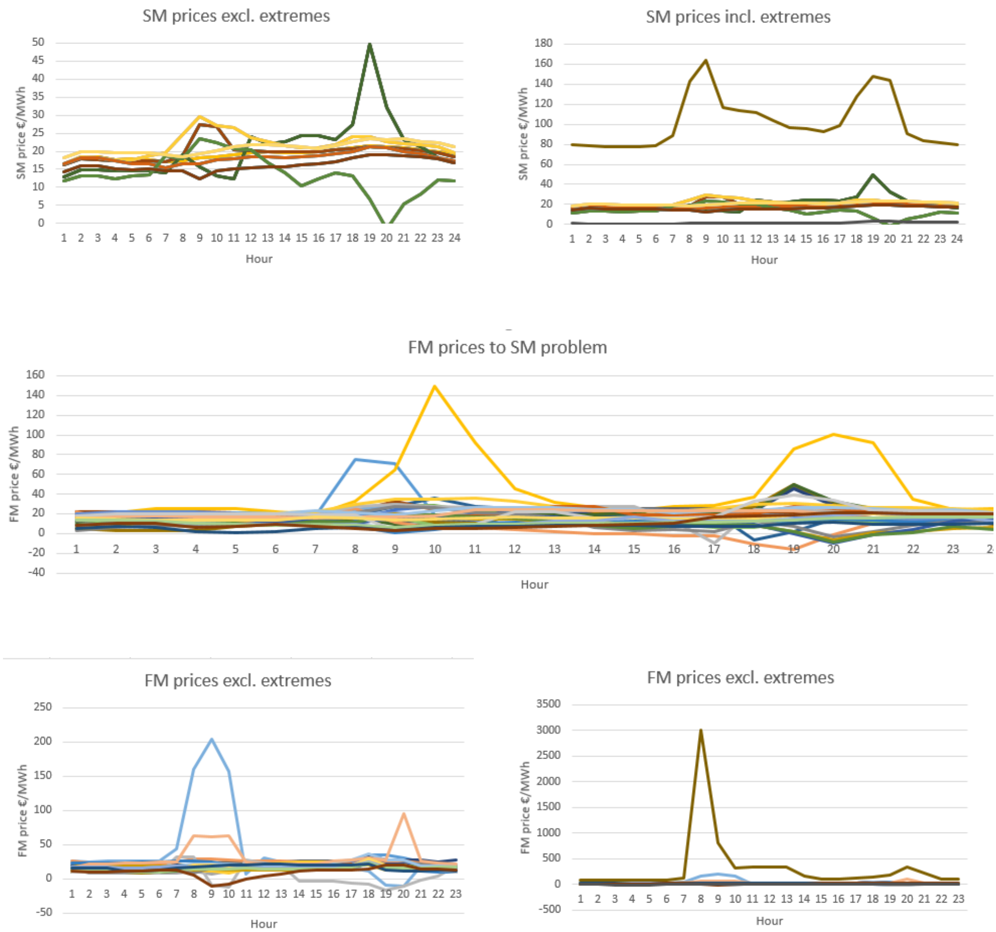


*Figure 4.17. Examples of scenarios to the SM and FM problems*

# Appendix 4.C. Bid decisions for one day

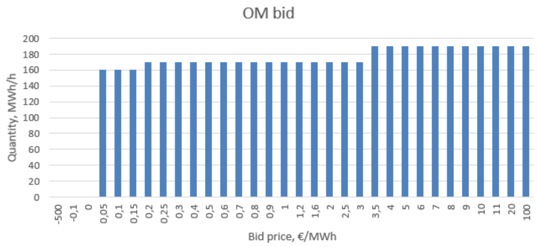


*Figure 4.18. OM bid for week 2 2016*

| Spot up | -500 | -1 | 0 | 1 | 19 | 20 | 21 | 34 | 35 | 36 | 49 | 50 | 51 | 94 | 95 | 96 | 104 | 105 | 106 | 3000 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 20,0 | 20,0 | 20,0 | 40,0 | 140,0 | 140,0 | 140,0 | 190,0 | 190,0 |
| 2 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 20,0 | 20,0 | 20,0 | 40,0 | 140,0 | 140,0 | 140,0 | 190,0 | 190,0 |
| 3 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 20,0 | 20,0 | 20,0 | 40,0 | 140,0 | 140,0 | 140,0 | 190,0 | 190,0 |
| 4 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 10,0 | 10,0 | 10,0 | 40,0 | 140,0 | 140,0 | 140,0 | 190,0 | 190,0 |
| 5 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 10,0 | 10,0 | 10,0 | 40,0 | 140,0 | 140,0 | 140,0 | 190,0 | 190,0 |
| 6 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 10,0 | 10,0 | 10,0 | 20,0 | 20,0 | 20,0 | 20,0 | 20,0 | 20,0 |
| 7 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 20,0 | 20,0 | 20,0 | 20,0 | 20,0 | 20,0 | 20,0 | 20,0 |
| 8 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 10,0 | 10,0 | 10,0 | 20,0 | 20,0 | 20,0 | 20,0 | 20,0 | 20,0 | 20,0 | 20,0 |
| 9 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 20,0 | 20,0 | 20,0 | 20,0 | 20,0 | 20,0 | 20,0 | 20,0 | 20,0 |
| 10 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 10,0 | 10,0 | 10,0 | 20,0 | 20,0 | 20,0 | 20,0 | 20,0 |
| 11 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 20,0 | 20,0 | 20,0 | 20,0 | 20,0 | 20,0 | 20,0 |
| 12 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 10,0 | 10,0 | 10,0 | 20,0 | 20,0 | 20,0 | 20,0 | 20,0 |
| 13 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 10,0 | 10,0 | 10,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 |
| 14 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 |
| 15 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 20,0 | 20,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 |
| 16 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 20,0 | 20,0 | 20,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 |
| 17 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 20,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 |
| 18 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 20,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 |
| 19 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 20,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 |
| 20 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 20,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 |
| 21 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 |
| 22 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 |
| 23 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 |
| 24 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 20,0 | 20,0 | 20,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 | 30,0 |

| Spot d | -500 | -1 | 0 | 1 | 19 | 20 | 21 | 34 | 35 | 36 | 49 | 50 | 51 | 94 | 95 | 96 | 104 | 105 | 106 | 3000 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 63,0 | 63,0 | 63,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 2 | 63,0 | 63,0 | 20,5 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 3 | 63,0 | 63,0 | 19,2 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 4 | 63,0 | 63,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 5 | 63,0 | 63,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 6 | 63,0 | 63,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 7 | 62,0 | 62,0 | 28,5 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 8 | 62,0 | 62,0 | 62,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 9 | 5,0 | 5,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 10 | 5,0 | 5,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 11 | 5,0 | 5,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 12 | 5,0 | 5,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 13 | 5,0 | 5,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 14 | 5,0 | 5,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 15 | 5,0 | 5,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 16 | 5,0 | 5,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 17 | 5,0 | 5,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 18 | 5,0 | 5,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 19 | 5,0 | 5,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 20 | 5,0 | 5,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 21 | 5,0 | 5,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 22 | 5,0 | 5,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 23 | 5,0 | 5,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 24 | 5,0 | 5,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |

*Figure 4.19. SM bids for 15.01.2016*

| Flex u | -500 | -1 | 0 | 1 | 19 | 20 | 21 | 34 | 35 | 36 | 49 | 50 | 51 | 94 | 95 | 96 | 104 | 105 | 106 | 3000 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 20,0 | 20,0 | 40,0 | 40,0 | 40,0 | 40,0 | 40,0 | 40,0 | 40,0 |
| 2 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 20,0 | 20,0 | 40,0 | 40,0 | 40,0 | 40,0 | 40,0 | 40,0 | 40,0 |
| 3 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 20,0 | 20,0 | 40,0 | 40,0 | 40,0 | 40,0 | 40,0 | 40,0 | 40,0 |
| 4 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 10,0 | 10,0 | 40,0 | 40,0 | 40,0 | 40,0 | 40,0 | 40,0 | 40,0 |
| 5 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 10,0 | 10,0 | 40,0 | 40,0 | 40,0 | 40,0 | 40,0 | 40,0 | 40,0 |
| 6 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 10,0 | 10,0 | 40,0 | 40,0 | 40,0 | 40,0 | 40,0 | 40,0 | 170,0 |
| 7 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 20,0 | 35,0 | 170,0 |
| 8 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 20,0 | 160,0 | 170,0 |
| 9 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 20,0 | 160,0 | 170,0 |
| 10 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 20,0 | 160,0 | 170,0 |
| 11 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 6,7 | 6,7 | 6,7 | 6,7 | 6,7 | 6,7 | 6,7 | 31,7 | 170,0 |
| 12 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 25,0 | 170,0 |
| 13 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 15,0 | 170,0 |
| 14 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 25,0 | 170,0 |
| 15 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 20,0 | 20,0 | 20,0 | 20,0 | 30,0 | 30,0 | 30,0 | 30,0 | 170,0 |
| 16 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 20,0 | 20,0 | 20,0 | 20,0 | 20,0 | 20,0 | 20,0 | 20,0 | 170,0 |
| 17 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 100,0 | 100,0 | 115,0 | 115,0 | 170,0 |
| 18 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 20,0 | 160,0 | 170,0 |
| 19 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 100,0 | 100,0 | 100,0 | 100,0 | 160,0 | 170,0 |
| 20 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 10,0 | 10,0 | 20,0 | 20,0 | 20,0 | 20,0 | 20,0 | 20,0 | 20,0 | 90,0 | 170,0 |
| 21 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 45,0 | 90,0 | 170,0 |
| 22 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 20,0 | 20,0 | 20,0 | 20,0 | 170,0 |
| 23 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 10,0 | 10,0 | 10,0 | 10,0 | 10,0 | 10,0 | 20,0 | 20,0 | 20,0 | 20,0 | 170,0 |
| 24 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 20,0 | 20,0 | 40,0 | 40,0 | 40,0 | 40,0 | 170,0 |

| Flex dc | -500 | -1 | 0 | 1 | 19 | 20 | 21 | 34 | 35 | 36 | 49 | 50 | 51 | 94 | 95 | 96 | 104 | 105 | 106 | 3000 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 43,0 | 43,0 | 5,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 2 | 43,0 | 43,0 | 5,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 3 | 63,0 | 63,0 | 5,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 4 | 63,0 | 63,0 | 5,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 5 | 63,0 | 63,0 | 5,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 6 | 43,0 | 43,0 | 5,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 7 | 42,0 | 42,0 | 5,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 8 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 9 | 5,0 | 5,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 10 | 5,0 | 5,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 11 | 5,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 12 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 13 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 14 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 15 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 16 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 17 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 18 | 5,0 | 5,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 19 | 5,0 | 5,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 20 | 5,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 21 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 22 | 15,0 | 15,0 | 15,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 23 | 15,0 | 15,0 | 15,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |
| 24 | 15,0 | 15,0 | 15,0 | 5,0 | 5,0 | 5,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 |

*Figure 4.20. FM bids for 15.01.2016*

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Paper 4

Stig Ødegaard Ottesen, Magnus Korpås and Asgeir Tomasgard:

# *Direct control methods for smart electric vehicle charging at grid constrained charging sites*

*Submitted to international, peer-reviewed journal*

# Chapter 5. Direct control methods for smart electric vehicle charging at grid constrained charging sites

## Abstract

Simultaneous charging of plug-in electric vehicles (PEVs) may lead to overload and voltage problems in distribution grids and in the electric infrastructure at charging sites. An alternative to investing in increased grid capacity is to control the charging power to each PEV, so called smart charging. In this paper, we propose two different smart charging methods for charging sites with grid constraints and where PEVs are parked over a long time. The aim is at maximizing the delivered charging energy without violating the grid constraints. The first method is a rule-based algorithm, which is easy to implement, while the second is optimization-based and requires information about the PEV drivers' preferences regarding charging demand and time to departure. In a case study based on real data, we analyze how the two methods perform in meeting the demand. In very constrained and only slightly constrained situations, they perform equally good, else the optimization-based is best. Further, the difference in performance between the methods decrease when introducing storage units and local generation. Next, we analyse how the two methods can be used for reducing the necessary grid capacity and still meet all demand. We find that both methods give considerable reductions, but that the optimization-based outperforms the rule-based in all datasets. Further, adding smart charging to a storage solution or vice versa gives only marginal improvement. As a benchmark, we calculate optimal solutions under perfect foresight. The findings indicate that our optimization-based method delivers solutions close to the ones with perfect foresight.

## 5.1. Introduction

According to the International Energy Agency (2009), the transport sector currently accounts for about 23% of energy-related $CO_2$ emissions globally. This is expected to increase by nearly 50% within 2030 and more than 80% by 2050 in absence of new policies. Electrification of vehicles by battery electric vehicles (BEV) and plug in hybrid electric vehicles (PHEV) is one of the most promising options to decarbonize road transport. In Norway, the authorities have introduced strong incentives to promote BEVs. The incentives include exemption from import tax and VAT, free toll roads, free parking and access to bus lanes to mention a few (Bjerkan, Nørbech, & Nordtømme, 2016; Figenbaum, Assum, & Kolbenstvedt, 2015; Haugneland, Bu, & Hauge, 2016; Mersky et al., 2016). Because of these policies, Norway has the largest number of BEVs per capita in the world. In 2015 more than 20% of all new vehicles sold were BEVs, and by the end of July 2016 there were 86 000 BEVs in Norway. Adding 23 000 PHEVs to this number, 4% of the total Norwegian car fleet is chargeable (EV Norway, 2016). The Norwegian parliament is currently discussing policies targeting that almost 100% of all new sold cars in 2025 should be emission free, meaning that the electrification will continue to grow (The Norwegian Ministry of Petroleum and Energy, 2016).

It is well documented that the extra load from simultaneous charging of PEVs may lead to challenges in the electricity system. Such problems in particular come in parts of the distribution grid with a large population of PEVs or where the grid is weak, and lead to thermal overloads, voltage deviations and increased electrical losses (Clement-Nyns, Haesen, & Driesen, 2010; Galus et al., 2013; Lee et al., 2015; Lopes, Soares, & Almeida, 2011). Norway is already starting to experience such situations (Brandslet, 2015; NRK, 2014). Several studies analyse grid impact from future higher PEV adoption levels (Allard et al., 2013; Bremdal & Grasto, 2014; Sagosen & Molinas, 2013; Seljeseth, Taxt, & Solvang, 2013), concluding that the distribution grid must be reinforced or that the charging processes should be controlled. The latter, denoted smart charging, is proposed since reinforcing the distribution grid to be able to handle worst case scenarios might be economically inefficient and have low utilization levels (Teng, Aunedi, & Strbac, 2016). Avoiding network reinforcements may also be obtained by installing separate battery banks and distributed generation units (Sbordone et al., 2015).

PEVs may charge at home, at a commercial fast charging station or at a parking lot. The focus in this paper is on the latter. We examine how smart charging can be used to utilize the available capacity to meet the drivers' preferences as much as possible, without violating the grid limitations. A crucial question is how to design the control methods for the operation of smart charging, alone or in combination with battery banks and distributed generation. Furthermore, if all charging demand can not be met, the capacity should be distributed between the PEVs in a way that minimizes the dissatisfaction and is perceived as fair from the perspective of the drivers.

Control methods can be categorized into indirect and direct control (Kostková et al., 2013; Wu, 2013), also denoted decentralized and centralized control.

Indirect control is a mechanism where a central agent sends a signal to which the customers respond. A classic example in the electricity market is the Time of Use (ToU) tariff, where the Distribution System Operator (DSO) sets high prices for hours with high load and low prices otherwise. The customers are then motivated to shift load away from high load periods and peaks are reduced. In the case of smart charging, a Charging Service Manager (CSM) (Sundstrom & Binding, 2012) sends a price signal or a menu of prices and the PEV drivers individually decide the charging schedule based on this list and their own preferences (Heussen et al., 2012; Soltani, Kim, & Giannakis, 2015). A high price will be set for periods with limited capacity. An advantage with indirect control is that it requires little communication infrastructure between the CSM and the PEV and that the drivers themselves make the decisions. A drawback is that there is no way that the response can be guaranteed. A challenge is also how to establish dynamic price menus with different prices for different qualities (time, power) that yield the wanted result. In Norway, charging services are currently either offered for free, according to charged energy or on a per minute basis with differentiation on power levels. To our knowledge, differentiated charging prices are not used for indirect control in grid constrained situations. However, with even higher shares of PEVs in the future, we expect innovative business models based on indirect control to be introduced.

Direct control is the mechanism where a central agent remotely controls customers' equipment. In the electricity sector a typical example is a DSO that remotely turns off appliances at a customer's premises according to a flexibility contract (Kostková et al., 2013). In the context of this article, direct control is used when a central agent (the CSM) decides the charging power to each PEV. Since this is a coordinated decision, it is easier to obtain the desired response. However, this mechanism requires more advanced technical infrastructure to retrieve information from the car and the driver and to send control commands to the PEV or the charging point.

This paper deals with direct control of charging at parking lots where many PEVs are parked over a long time and are charged simultaneously, for instance at work-places, shopping malls, hospitals or airports. Further, we are interested in situations where the total power capacity is limited so that it is not possible to charge all PEVs at full power simultaneously. Experiences from Norway show that this problem already exists. Salto (2016) shows a real-life example where a parking lot in Oslo is reconstructed to offer charging services for up to 86 PEVs, but where simultaneous charging at full power is possible for less than half the charging points, due to grid constraints in the electrical infrastructure at the parking lot. More importantly, this is a persisting problem. With current technologies and cost levels, it may not be sound or welfare maximising to dimension the grid capacity of a parking lot at a company or shopping mall in such a way that all vehicles can be charged at full power simultaneously.

Two different decision support methods for direct control is proposed in this paper, where one method requires that the PEV driver shares information with the CSM, while the other does not. To make the methods applicable in real life, we take into account that the information about arrivals, departures and possibly preferences is revealed gradually. We analyse and compare the performance of each method. As a benchmark, we also analyse a situation with uncontrolled charging and another assuming perfect foresight.

The remainder of the paper is organized as follows: Section 5.2 describes direct smart charging methods in the literature. Section 5.3 outlines the charging site model and the smart charging methods. Section 5.4 contains the case study.

## 5.2. Direct smart charging methods in the literature

An extensive number of recent articles propose methods for smart charging. They have different actor perspectives which briefly can be divided into system operators, aggregators, fleet operators and PEV users. Furthermore, the different articles present different objectives, such as cost minimization, welfare maximization, emission reduction, maximization of renewable generation utilization, power loss minimization, battery performance improvement and load variation minimization. A recent review of direct control scheduling methods for integrating PEVs in electricity systems is given in Yang, Li, & Foley (2015).

We find that most of the papers are not applicable for the CSM's problem in cases with grid constraints. However, some relevant articles are described below.

A simple approach to avoid violations of grid constraints is the traditional scheduling method *first-come-first-serve* (FCFS): each time a new PEV connects, the CSM checks whether there is available grid capacity. If not, the PEV is put in the end of a waiting queue and the charging is delayed. When a car finishes charging, the first car in the queue gets served. This method is benchmarked in several of the references below. Papadopoulos et al. (2012) takes this one step further, by serving the PEVs according to a priority list. The method manages to avoid constraint violation, but the article does not analyse to what extent the charging demand is met. Amoroso & Cappuccino (2011) consider not only delaying the charging, but also charging at reduced power levels (variable rate) to mitigate constraints. Based on user preferences, priorities are recalculated in each time-slot.

Optimization models are frequently applied in smart charging problems. Akhavan-Rezai et al. (2016) model a parking lot where PEVs are optimally charged in order to maximize the owners' satisfaction in terms of the energy delivered, without violating grid constraints. The decision making algorithm is based on scored charging priority in two steps: First, prioritizations are calculated based on fuzzy logic. Secondly, the number of high scored PEVs are maximized in a MILP. A similar problem is studied in Kuran et al. (2015), that propose a model for a parking lot with the objective to maximize the total number of PEVs fulfilling their recharging requirements at the time of departure. This model prerequisites information from the PEVs. The problem is formulated as a MILP. However, their objective function maximizes the number of PEVs that are fully charged, and hence will avoid partially recharging of some. The result will then be that some cars get no recharging at all, which probably will be perceived as unfair. Rezaei, Frolik, & Hines (2014) introduce the concept of urgent charging, meaning that in constrained periods, drivers' who have selected urgent charging are prioritized above others.

In these types of decision problems, a key issue is that information about PEVs connecting and disconnecting will not be known in advance, but will be gradually revealed. This is not clearly discussed in the papers referenced above. Furthermore, getting the true information from the drivers when they arrive, might be a challenge.

Therefore, we want to synthesize some of the concepts outlined above to define and analyse two smart charging methods, where one does not require information from the PEV and the driver, while the other method does. Our target is that the proposed models should be possible to implement in a real-life operational setting. We then analyse how the different models perform in satisfying the PEV drivers' charging demands in constrained situations. Further, we analyse how much each method will contribute in reducing the needed capacity while still delivering all demanded charging energy. We also include scenarios with a given setup of battery banks and solar panels to analyse how they influence the results.

To benchmark our methods, we compare with a non-controlled strategy and an optimization-based strategy assuming perfect foresight.

## 5.3. The charging site model and the scheduling methods

We define a charging site as a location where one or multiple PEVs can charge their batteries by connecting to a charging point, which can be an ordinary socket or a more advanced charging station. Each charging point is characterized with a maximum charging power (kW), and we assume that the charging power can be controlled to any level between 0 and the maximum. The charging site has a total capacity limit (maximum power) for electricity imported from the grid. Such a limit can be a technical limit from fuse sizes, cables, circuit breakers, substation transformer capacity, voltage level or congestion in overlying grid. In principle the limit can also be economic because of a tariff constraint. We include the concept of prioritized charging, meaning that in cases with limited total capacity, some charging points are prioritized above others. This might be relevant for charging points intended for visitors at workplace parking lots.

In addition to the charging points, the charging site can have one or multiple separate storage units, like battery banks and one or multiple renewable generation units, producing electricity from sun or wind. Such generation is modelled as uncontrollable, but will influence the scheduling decisions.

Figure 5.1 illustrates the total charging site model, including the charging points (CPs), storage units (SUs) and generating units (GUs). The storage and generating units are within a dashed rectangle to illustrate that these are optional in the model. The fuse symbol illustrates the capacity constraint for the charging site.

The starting point for this paper is that uncontrolled PEV charging, also denoted *Dumb charging*, will break the constraint and hence lead to an infeasible situation. The CSM's task is to schedule the PEV charging process and the charging and discharging of the storage units.

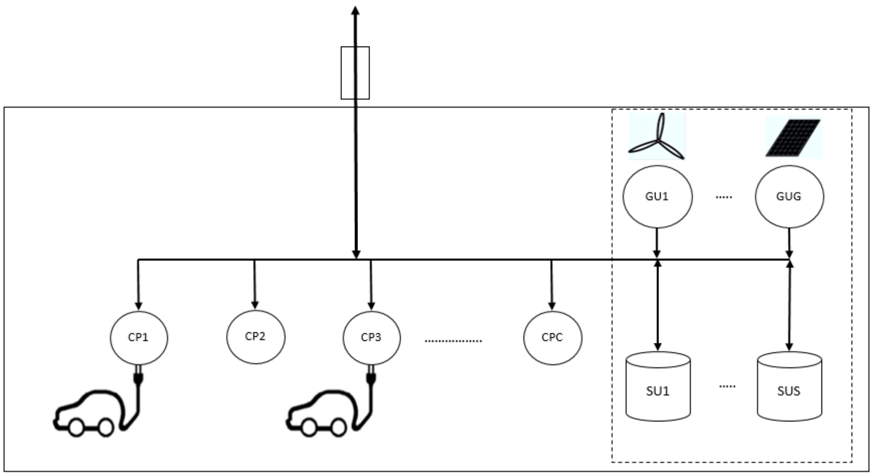


*Figure 5.1. A general representation of the charging site*

## The rule-based method

The rule-based scheduling method does not require any information exchange from the driver or the car to the CSM. Further, this method is myopic, meaning that it only considers the "here-and-now" situation without looking backwards in history or forward into the future. Hence it is easy to implement.

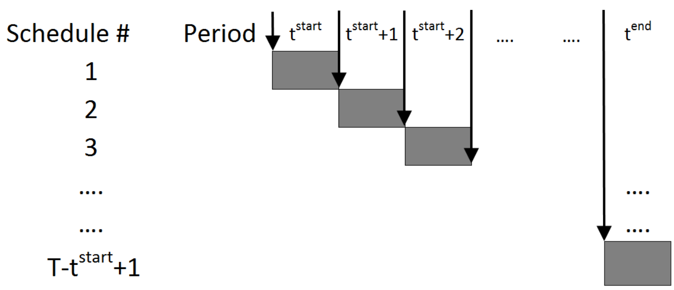


*Figure 5.2. Decision process for the rule-based method*

Figure 5.2 illustrates the decision process. When the first period $t^{start}$ is entered, we receive information about connections and generation in this period, illustrated by the left arrow. We make schedule number 1, valid for period $t^{start}$, and implement this. Next, when period $t^{start}+1$ is entered, we receive new information (disconnections of PEVs and connected PEVs that are fully charged in period $t^{start}$, new connections and generation in $t^{start}+1$). Based on this information, we make schedule number 2 valid for period $t^{start}+1$, and implement this. The process is repeated through all the periods until period $t^{end}$.

In cases where a grid constraint exists, the rule-based method will first try to discharge storage units if possible. If the problem still exists, it will regulate down the charging power for the normal mode charging points. Charging power to each charging point will be reduced pro-rata (equal fraction to each charging point), until the problem is relieved. If there still is a problem when the normal mode charging points are regulated down to 0 power, the same procedure will be repeated for the priority mode charging points. A flow chart for the method is shown in Figure 5.3.

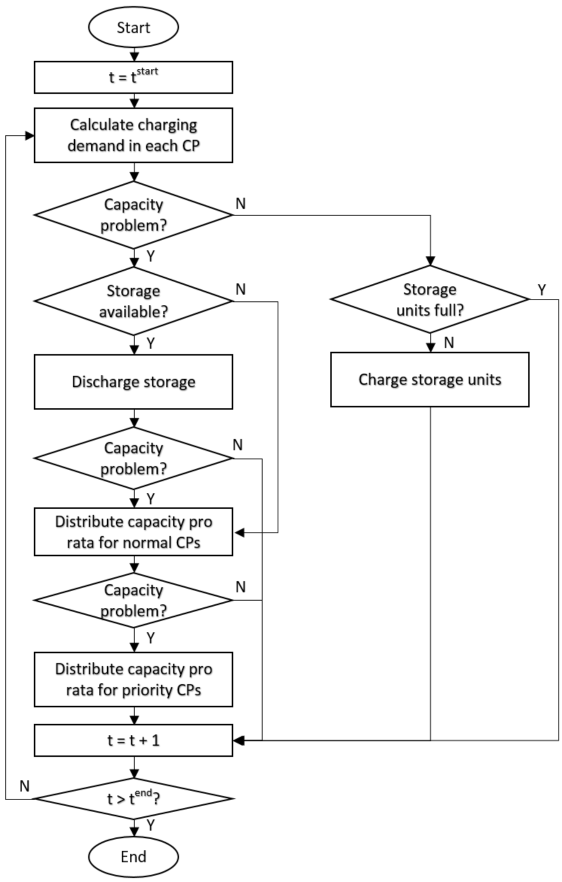


*Figure 5.3. Flow chart for the rule-based scheduling method*

## The Optimization-based method

In a typical charging session, a PEV starts charging when it is plugged in, and the charging is often completed before the vehicle disconnects and departs (Kara et al., 2015). Such cases represent flexibility, since the vehicle could have been charged in later periods, and the driver would still be satisfied. In the optimization-based method, this flexibility is utilized by moving some of the charging to later periods. Then the target is to increase the total delivered charging energy, compared to the rule-based method. To get information about available flexibility, we assume that the PEV drivers submit their preferences regarding departure time and charging demand (Xu et al., 2014; Zakariazadeh, Jadid, & Siano, 2015), for instance through an app. For simplicity reasons we assume that the PEV drivers reveal their true preferences. This might be obtained through a price model where the driver is compensated for being connected more than the minimum needed periods, but this is outside the scope of this article. Compared to the rule-based method we are now able to look into the future for the already connected PEVs and to use the additional information to make more optimal decisions.

The decision process for the optimization-based method is quite similar to the process for the rule-based method, see Figure 5.2. Though, while each schedule from the rule-based method only takes one period (the current) into account and makes a decision for this, the optimization based looks into all periods from current until the end of the planning horizon. Inter-relations between the different periods will then be taken into account. This is possible since we now receive information about preferred disconnection period and charging demand. Decisions are made for all the periods, but only implemented for the current period. Referring to Figure 5.2, schedule number 1 will now be valid for all the periods between $t^{start}$ and $t^{end}$, but we implement only the decisions for period $t^{start}$. Similarly, we step through all the periods in a receding planning horizon manner.

### Objective function

The basic objective with the optimization based model is to minimize customer dissatisfaction. This is covered in the first line in the objective function presented in Equation (5.1):

$$\min z = \alpha \sum_{c \in C} \sum_{y \in Y} \left( P^{pri} \Delta_{c,y}^{pri} + P^{norm} \Delta_{c,y}^{norm} \right) + \beta \sum_{y \in Y} \left[ \sum_{c \in C^P} \left( \frac{\Delta_{c,y}^{pri}}{E_{c,y}} \right)^2 + \sum_{c \in C^N} \left( \frac{\Delta_{c,y}^{norm}}{E_{c,y}} \right)^2 \right] \\ + \gamma \sum_{l \in L} (\sigma_{l,t^{curr}}^{out} - \sigma_{l,t^{curr}}^{in}) - \varphi \sum_{c \in C} \chi_{c,t^{curr}} \tag{5.1}$$

Here, $\Delta_{c,y}^{pri}$ and $\Delta_{c,y}^{norm}$ are the deviations between the demanded and delivered charging energy in each charging point *c* and charging session *y*, where each charging point is in either priority mode (*pri*) or normal mode (*norm*). The deviations are multiplied with the corresponding penalty factors $P^{pri}$ and $P^{norm}$, summed, and finally multiplied with the deviation weight $\alpha$. Different charging sessions are included to handle that a charging point can serve several cars in a sequence.

The second term is a smoothing term which sums the squared relative charging demand deviations $\left( \frac{\Delta_{c,y}^{pri}}{E_{c,y}} \right)^2$ and $\left( \frac{\Delta_{c,y}^{norm}}{E_{c,y}} \right)^2$ over all charging points and charging sessions multiplied with the smoothing weight $\beta$. $E_{c,y}$ is the demanded charging energy for charging in charging point *c* in charging session *y*. This term ensures distribution of the deviations between PEVs. Otherwise, the model would be indifferent to how to distribute the deviation. Hence, in a situation with two equal PEVs (i.e. with the same charging demand, maximum power and disconnection period), the model might allocate all the deviation to one of the PEVs.

In situations where the model is able to meet all charging demand, the two first terms in the objective function will equal zero.

The third term minimizes the discharging $\sigma_{l,t^{curr}}^{out}$ or maximizes the charging of storage units $\sigma_{l,t^{curr}}^{in}$ for the current period $t^{curr}$, summed over all units *l*, multiplied with the weight factor $\gamma$. This term is needed to avoid that the storage units are emptied early in the horizon, before the capacity problem arises, or similarly to motivate to fill the storage early in the horizon to be able to meet possibly higher demand later. The last term maximizes the charging power $\chi_{c,t^{curr}}$ in all charging points in current period summed over all charging points *c*, multiplied with the weight factor $\varphi$. This term is needed to force the model to utilize as much as possible of the available charging capacity in the current period. Without this term, the model could choose to delay charging when making a plan early in the planning horizon. Then, when new PEVs connect, the capacity might be limited and delivering all energy could be impossible.

Since the main target with the model is to minimize charging demand deviations, the α should be the largest of the weight parameters.

## Charging point constraints

A PEV connects to a charging point *c* in the start of period $T_{c,y}^{start}$ and disconnects in the end of period $T_{c,y}^{end}$. Charging power $\chi_{c,t}$ to each charging point *c* in each period *t* must be below maximum power $X_c^{max}$:

$$\chi_{c,t} \leq X_c^{max}, \quad c \in C, t \in T \tag{5.2}$$

Delivered charging energy $\varepsilon_c^{dce}$ (in kWh) to a PEV in the end of current period is equal to state of delivery in the previous period plus charging during current period divided by the number of periods in one hour $N$.

$$\varepsilon_{c,t}^{dce} = \varepsilon_{c,t-1}^{dce} + \chi_{c,t} / N, \quad c \in C, t \in T(y) \tag{5.3}$$

Here, *T(y)* includes all periods between start $T_{c,y}^{start}$ and end period $T_{c,y}^{end}$ for charging point *c* and charging session *y*. Delivery deviation $\Delta_{c,y}$ for charging point *c* and charging session $y$ is defined as the difference between demanded $E_{c,y}$ and real delivered energy at the end of the last period $T_{c,y}^{end}$ for priority and normal mode charging points, respectively:

$$\Delta_{c,y}^{pri} = E_{c,y} - \varepsilon_{c,t}^{dce}, \quad c \in C^{pri}, t = T_{c,y}^{end}, \tag{5.4}$$

$$\Delta_{c,y}^{norm} = E_{c,y} - \varepsilon_{c,t}^{dce}, \quad c \in C^{norm}, t = T_{c,y}^{end}. \tag{5.5}$$

## Charging site constraints

In each period $t$ total electricity imported to $\chi_t^{import}$ or exported from $\chi_t^{export}$ the charging site, must balance sum charging power $\chi_{c,t}$ to each charging point *c* and $\sigma_{s,t}^{in}$ to each storage unit *s*, minus discharging $\sigma_{s,t}^{out}$ from storage unit *s* and generation $I_{g,t}$ from generation units *g*:

$$\chi_t^{import} - \chi_t^{export} = \sum_{c \in C} \chi_{c,t} + \sum_{s \in S} \sigma_{s,t}^{in} - \sum_{s \in S} \sigma_{s,t}^{out} - \sum_{g \in G} I_{g,t}, \ t \in T \tag{5.6}$$

In each period the charging site will either import or export:

$$\delta_t^{import} + \delta_t^{export} \leq 1, \quad t \in T \tag{5.7}$$

Total electricity to or from charging site must be below capacity limit:

$$\chi_t^{import} \leq \delta_t^{import} X^{cap}, \quad t \in T \tag{5.8}$$

$$\chi_t^{export} \leq \delta_t^{export} X^{cap}, \quad t \in T \tag{5.9}$$

For formulations of the storage unit constraints, we refer to Ottesen & Tomasgard (2015).

# 5.4. Case study

## Charging site and input data

We illustrate the properties of the models and analyse their performances in a case study based on a projected charging site outside a Norwegian office building. The reason for choosing an office building is that many of the cars are parked over a long time, and are therefore expected to provide charging flexibility. The site consists of 14 charging points: 6 points with 3.7 kW maximum charging power, 5 with 7.4 kW and finally 3 with 11 kW. The last 3 charging points are intended for visitors and hence given priority in cases with capacity limitations.

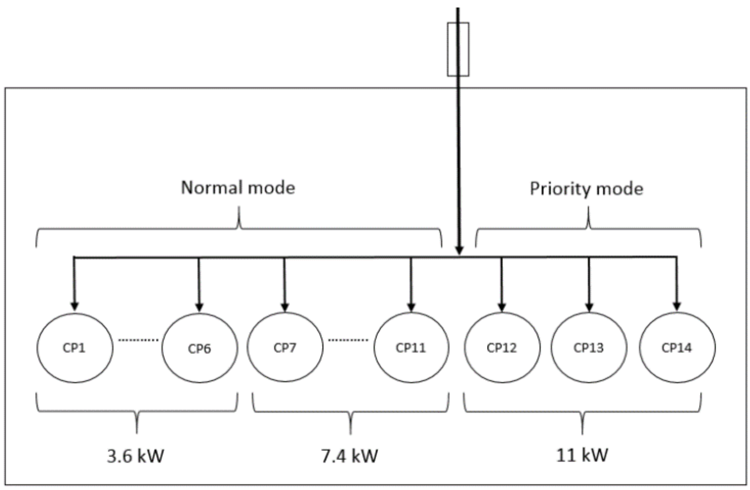


*Figure 5.4. Case study charging site*

Real data about charging sessions is received from Fortum Charge & Drive[22] for a charging site at a similar type of building. We have split our planning horizon into 15 minutes' time intervals. The full dataset consists of 303 charging sessions where the average charging volume is 12.2 kWh and the average connection duration is 4 hours and 40 minutes. Based on these data we have generated four different datasets with charging sessions for one day: Dataset 1 *Average day* has statistical properties similar to the full dataset, i.e. the average charging demand and connection duration for the sampled dataset is close to those for the full dataset. Total charging demand is 173 kWh. Next, we have generated three *High demand*-datasets, each

[22] https://chargedrive.com/

with a demand approximately twice the demand in dataset 1, but with different charging profiles. Figure 5.5 presents charging profiles for each dataset if no capacity limit. Detailed information about connections, disconnections and charging demands are presented in Table 5.1 in Appendix 5.A.

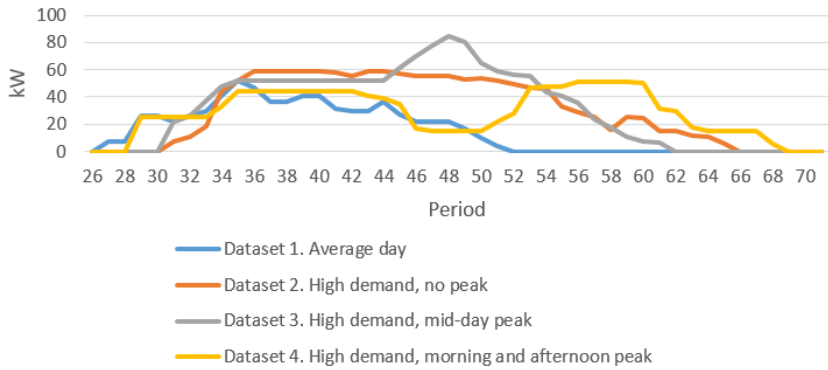


*Figure 5.5. Unconstrained charging profile for each dataset*

## Analytical approaches

We compare four different charging strategies:

1. DUMB - Uncontrolled method, meaning that the EVs start charging as they connect and stop charging as they disconnect or are fully charged
2. RULE - Rule-based method according to the description in section 5.3
3. OPTI - Optimization-based method, where decisions are made based on available information according to the description in section 5.3
4. PERF - Optimization-based method, with perfect foresight

Since we will never have perfect foresight in real life, the last method is included just to analyze how well RULE and OPTI delivers compared to the theoretical best solution. We denote method 2 – 4 *Smart Charging*.

Furthermore, we include a separate storage unit and a solar PV panel. The parameters are set the following way: Maximum storage energy content (43 kWh) is equal to ¼ of average charging demand for one day, while maximum charging and discharging capacities (23 kW in and out) are set equal to ¼ of sum installed charging point capacity. The solar panel is similar to the ones that have been installed in 2015 at the island group Hvaler[23], located Southeast in Norway. We assume a 50 $m^2$ panel area, which gives 7.75 kWp. Further, we use metered solar generation for a typical day at Hvaler in September as input to our analyses. An overview of input-parameters are given in Appendix 5.A. Notice that optimal sizing of storage and PV panels is a task outside the scope of this paper. We have included such units in this study only to analyse how they impact the operational decisions.

We analyse 12 different combinations of charging method, storage and generation:

1.1 DUMB
1.2 DUMB + storage
1.3 DUMB + storage + generation
2.1 RULE
2.2 RULE + storage
2.3 RULE + storage + generation
3.1 OPTI
3.2 OPTI + storage
3.3 OPTI + storage + generation
4.1 PERF
4.2 PERF + storage
4.3 PERF + storage + generation

We use the combinations to analyse two measures from two research questions:

1. **How well will the different methods meet the PEV charging demand if the capacity limit is given?** The measure is the percentage of demanded charging energy that is delivered and is relevant in an operational setting where the setup of the charging site is given.

2. **What is the minimum capacity needed (in kW) to meet all PEV charging demand?** This is relevant when designing the setup of a charging site. Although that is not the target with this paper, we include it to evaluate how the different methods perform.

To answer research question 1, we have chosen the following approach: We start out by finding the minimum capacity limit where PERF is able to deliver exactly 100 %, which can be interpreted as the lowest capacity limit where the charging site theoretically is able to deliver all demanded energy. Notice that there will be different limits for 4.1, 4.2 (with storage) and

[23] http://www.smartenergihvaler.no/sol/

4.3 (with storage and generation). Next, we calculate delivered charging energy for each combination 2.1 through 3.3. To simulate an extremely constrained situation, we next reduce the capacity by 50 % and repeat the calculations. Finally, we increase the capacity to 150 % and repeat the calculations to simulate a slightly constrained situation.

To answer research question 2, we iterate with different capacities and calculate demand not met until it turns to 0. Our target is to find how the different combinations 1.1 to 4.3 perform in terms of minimum capacity needed.

By performing these analyses, our goal is to obtain knowledge about capabilities of each method, to find structural differences between them and to quantify the value of each method in our datasets.

## Results

We start out with research question 1. First, we calculate the minimum capacity where PERF (4.1 – 4.3) is able to deliver 100 % of the demanded energy, see Table 5.3 for results. We use this limit and calculate how much of the demanded charging energy the other methods deliver. Note that *DUMB* will give congestion and hence infeasible solutions for all datasets. Figure 5.6 shows average values over all datasets, while detailed results for each dataset is presented in Table 5.4 to 5.6 in Appendix 5.B.

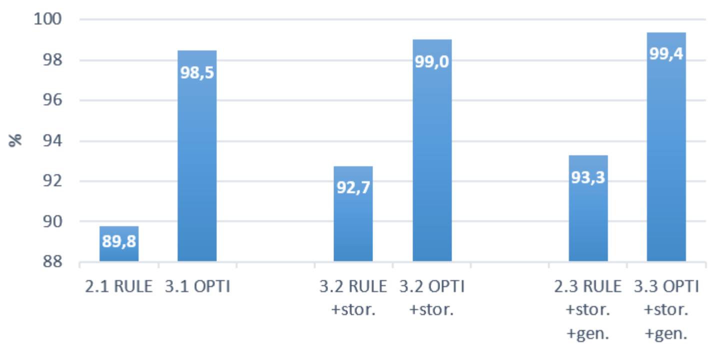


*Figure 5.6. Delivered demanded charging energy if PERF delivers 100 %*

We see that *OPTI* delivers close to 100 % in all combinations, while *RULE* delivers between 10.2 and 6.7 % lower. Notice that the delivery increases with storage and generation, due to more available flexibility, and that the difference between the methods decreases with storage and even more with generation. The reason is that *OPTI* is better at utilizing small amounts of flexibility.

Table 5.4 to 5.6 also show that in very constrained or only slightly constrained situations, *RULE* performs equally with *OPTI* and in line with *PERF*.

All the analyses show that *OPTI* delivers better than *RULE*. However, in the very limited situations, *RULE* delivers more prioritized demand than *OPTI* for some of the datasets in some of the technology combinations. An example is if all charging points are not yet connected and charging power must be reduced. *OPTI* may then see that it is possible to deliver all prioritized energy in later periods and decide not to deliver to the prioritized charging point in current period. Later, when more vehicles connect, it may be impossible to meet all prioritized demand. Since *RULE* always decides a pro rata reduction and starts with charging points in normal mode, it may deliver larger amounts of prioritized energy. This problem, that only happens in very constrained situations and only in some datasets, can be avoided by introducing forecasts, but we leave this topic to future research.

We continue with research question 2. For each of the four datasets, we analyse all combinations, each time calculating the lowest power limit that makes it possible to meet all demand. Figure 5.7 shows an overview of the results, where each bar shows the average value over all datasets.


*Figure 5.7. Minimum capacity limit to meet all charging demand*

Overall we see that a large reduction in minimum capacity limit is obtained by introducing smart charging (*2.1* or *3.1*) or a storage unit (*1.2*). Further, we see that by first including smart charging, the further improvement from adding a storage unit is small (when moving from *2.1* to *2.2* or from *3.1* to *3.2*). The reason is that when we go from *1.1 DUMB* and introduce either *2.1 RULE* or *3.1 OPTI*, we flatten the power profile, by large reductions in some periods and smaller reductions in other. Going to the next step means to reduce a flat power profile, which will require reductions in many of the periods. Hence, this action will require a larger energy volume [kWh] for each power unit [kW] that is reduced. Then it is the storage volume that limits the added reduction by going from *2.1* to *2.2* or from *3.1* to *3.2*. Notice also that the difference in performance between RULE and OPTI is decreasing when we add a storage and further when we also add generation.

Detailed results from each dataset are presented in Table 5.7 to 5.9. Observe that *OPTI* delivers a larger reduction compared to *RULE* in all datasets. However, how much better varies between the datasets. Particularly in dataset *3. High demand, mid-day peak*, *RULE* delivers a small reduction compared to *OPTI*. The reason is that the more complex the case is (in terms of many simultaneous PEVs connected and little flexibility available in some of the PEVs), the better *OPTI* performs compared to *RULE*.

An interesting observation is that *OPTI* delivers results close to *PERF* in all datasets, which means that the value of perfect information is close to 0. Remember that we have not included any forecast information, only information regarding departures for the connected vehicles.

## Discussion

Two simplifying assumptions are made regarding the charging process: First, we assume that the charging power can be continuously controlled between 0 and maximum level. In real life this is a semi-continuous process, where the charging current can be controlled in an interval, for instance between 1.8 and 3.7 kW (corresponding to 8 and 16 A in Norway), but where charging below 1.8 kW will not work (the limits vary between different car types). However, in cases where the decision is below 1.8 kW, the problem may be omitted by circling, for example a 1 kW decision in a 15 minutes' interval can be implemented by charging 2 kW in 7.5 minutes. Second, we assume that the charging profile over a charging cycle is linear so that the PEV battery can charge constant power from empty to full. In practise, a battery will not be able to receive maximum power when it is close to full. The shape of the charging profile varies between different car types, so this is difficult to model properly. A consequence of the simplification is that the calculated time to meet the demand is too short. On the other hand, the stress against the grid constraint will be smaller. This problem might be reduced by exchanging information about battery state of charge and the charging profile for each connected PEV to the CSM and use this as additional input to the scheduling algorithm. Since such information would be possible only for *OPTI*, we expect that this would increase the performance of *OPTI* compared to *RULE*.

Our findings indicate that the value of perfect information is close to zero. We believe that this conclusion might not hold in cases with more extreme charging demand, for instance if very many connect simultaneously in the afternoon, or in cases with larger amounts of solar generation. However, this will have a practical consequence only if it is possible to predict the events. Then, OPTI would benefit from this information. Likewise, we have run our analyses for one given solar PV profile. Although this is not known in advance, we have not analysed how different profiles might impact the scheduling decisions. In cases where perfect information has a value, a stochastic programming approach should be evaluated.

The objective function, Equation (5.1) includes four parameters that weight the different terms $(\alpha, \beta, \gamma, \varphi)$ and two for penalization of not met charging demand $(P^{pri}, P^{norm})$. Their values are listed in Table 5.2 in Appendix 5.A. Different values will of course affect the objective function values. However, as long as $\alpha$, the weight factor for deviations between delivered and demanded charging energy, is much greater than the other weight factors, and $P^{pri}$, the penalty for not delivering prioritized energy, is much greater than $P^{norm}$, our findings indicate that the decisions have little sensitivity to the parameter values.

Each hour is divided into periods of 15 minutes', which means that when a car connects to a charging point, it must wait until the start of the next period before charging can start. In worst case, the car must wait 15 minutes. When implementing the models in real life, the periods should probably be shorter.

## 5.5. Conclusion and future research

We propose decision-support models for scheduling the charging processes for PEVs at charging sites with grid constraints. In addition to the PEV charging processes, we analyse combinations with storage and generation units. We propose two different smart charging methods: A rule-based algorithm, which reduces charging power pro rata in constrained situations, and an optimization-based method, which requires information about the PEV drivers' expected departures and charging demand.

The case study shows that for a given setup of a charging site, the methods deliver equal volumes of charging energy in very constrained or only slightly constrained situations. Otherwise, the optimization-based delivers more. Further, analyses of how much each method is able to reduce the minimum capacity needed show that the optimization-based method outperforms the rule-based. We also find that the value of perfect information is negligible and that forecasting or stochastic programming will not add value.

Further research should include a pilot study of a real charging site run on real data over a long period of time. Shorter periods than 15 minutes should be considered. We have assumed a given set of storage and solar panel parameters, and further, that solar generation is known with certainty. Different setups of storage units and solar parameters should be evaluated, as well as how uncertain solar generation will influence the results. Integration with demand response possibilities in buildings close by the charging site, is also an issue that requires more research, in addition to vehicle-to-grid (V2G) capabilities.

We have assumed that the PEV drivers reveal their true preferences regarding charging demand and expected departure time, but we have not looked into how business models should be designed to achieve this. Nor have we investigated different price models for the charging to maximize profit for the CSM or to reach other targets like motivating drivers to extend or shorten their connection times. Finally, since we in this article have focused on direct control, we propose further research also for indirect control methods, where economic signals are used to achieve similar effects.

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# 5.6. Appendices

## Appendix 5.A. Input data to case study

*Table 5.1. Charging data*

| | | | 1. Average day | | | 2. High demand, no peak | | | 3. High demand, mid-day peak | | | 4. High demand, morning and afternoon peak | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Ch point | Max power | Mode | Con. period | Disc. period | Dem. [kW] | Con. period | Disc. period | Dem. [kW] | Con. period | Disc. period | Dem. [kW] | Con. period | Disc. period | Dem. [kW] |
| 1 | 3.7 | N | 33 | 61 | 7.5 | 35 | 63 | 16.2 | 32 | 64 | 16.2 | 35 | 63 | 21.0 |
| 2 | 3.7 | N | 29 | 60 | 15.7 | 35 | 70 | 9.8 | 31 | 63 | 19.8 | 35 | 70 | 9.8 |
| 3 | 3.7 | N | 35 | 70 | 9.8 | 56 | 71 | 6.6 | 33 | 63 | 20.0 | 56 | 71 | 6.6 |
| 4 | 3.7 | N | 30 | 56 | 13.5 | 54 | 66 | 6.7 | 34 | 60 | 24.0 | 54 | 66 | 6.7 |
| 5 | 3.7 | N | 32 | 57 | 11.5 | 43 | 61 | 9.9 | 35 | 64 | 9.9 | 43 | 61 | 13.6 |
| 6 | 3.7 | N | 42 | 53 | 2.7 | 32 | 63 | 8.9 | 31 | 48 | 14.9 | 35 | 63 | 8.9 |
| 7 | 7.4 | N | 51 | 52 | 1.1 | 36 | 62 | 36.0 | 31 | 62 | 36.0 | 29 | 47 | 29.7 |
| 8 | 7.4 | N | 29 | 44 | 13.6 | 33 | 58 | 32.1 | 33 | 52 | 32.1 | 51 | 70 | 32.1 |
| 9 | 7.4 | N | 29 | 48 | 14.8 | 34 | 64 | 49.7 | 48 | 64 | 25.7 | 34 | 64 | 49.7 |
| 10 | 7.4 | N | 35 | 64 | 7.5 | 34 | 64 | 41.5 | 34 | 60 | 41.5 | 29 | 47 | 31.5 |
| 11 | 7.4 | N | 27 | 38 | 6.6 | 31 | 61 | 34.4 | 31 | 61 | 34.4 | 52 | 70 | 30.4 |
| 12 | 11 | Pri. | 39 | 48 | 6.9 | 34 | 59 | 57.4 | 45 | 59 | 37.4 | 29 | 47 | 47.4 |
| 13 | 11 | Pri. | 34 | 66 | 42.7 | 50 | 59 | 22.2 | 46 | 57 | 22.2 | 53 | 65 | 22.2 |
| 14 | 11 | Pri. | 44 | 53 | 19.0 | 59 | 66 | 18.0 | 47 | 58 | 28.0 | 53 | 68 | 28.0 |

*Table 5.2. Objective function parameters*

| Parameter name | $\alpha$ | $\beta$ | $\gamma$ | $\varphi$ | $P^{pri}$ | $P^{norm}$ |
|---|---|---|---|---|---|---|
| Value | 10 | 2 | 1 | 1 | 5 | 1 |

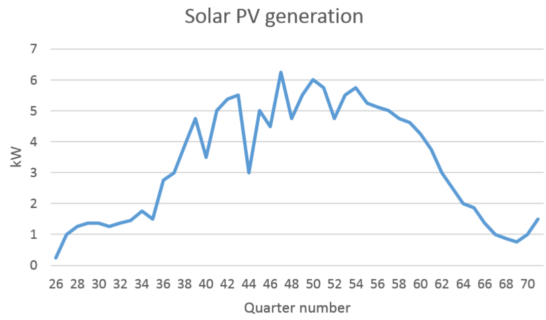


*Figure 5.8. Generation from solar panel*

# Appendix 5.B. Case study detailed results

*Table 5.3. Overview of minimum capacities [kW]*

| | Dataset 1. | Dataset 2. | Dataset 3. | Dataset 4. | Mean values all datasets |
|---|---|---|---|---|---|
| 4.1 PERF | 17.6 | 41.7 | 46.7 | 34.9 | 35.2 |
| 4.2 PERF | 12.9 | 35.9 | 40.3 | 28.6 | 29.4 |
| 4.3 PERF | 9.1 | 31.6 | 35.8 | 24.7 | 23.3 |

*Table 5.4. Percentage of demanded energy delivered with the different methods without storage or generation*

| Method | Grid Cap | Dataset 1. | Dataset 2. | Dataset 3. | Dataset 4. | Mean values all datasets |
|---|---|---|---|---|---|---|
| 4.1 PERF | 100 % | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |
| 3.1 OPTI | | 96.7 | 100.0 | 98.8 | 98.3 | 98.5 |
| 2.1 Rule | | 81.6 | 93.9 | 92.3 | 91.2 | 89.8 |
| 4.1 PERF | 50 % | 52.7 | 54.4 | 54.0 | 54.6 | 53.9 |
| 3.1 OPTI | | 52.7 | 54.4 | 54.0 | 54.6 | 53.9 |
| 2.1 Rule | | 51.2 | 52.7 | 54.0 | 54.5 | 53.1 |
| 4.1 PERF | 150 % | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |
| 3.1 OPTI | | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |
| 2.1 Rule | | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |

*Table 5.5. Percentage of demanded energy delivered with the different methods with storage*

| Method | Grid Cap | Dataset 1. | Dataset 2. | Dataset 3. | Dataset 4. | Mean values all datasets |
|---|---|---|---|---|---|---|
| 4.2 PERF | 100 % | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |
| 3.2 OPTI | | 99.9 | 98.2 | 98.4 | 99.5 | 99.0 |
| 2.2 Rule | | 87.6 | 94.7 | 93.0 | 95.6 | 92.7 |
| 4.2 PERF | 50 % | 64.4 | 59.7 | 58.8 | 57.5 | 60.1 |
| 3.2 OPTI | | 64.4 | 59.7 | 58.8 | 57.5 | 60.1 |
| 2.2 Rule | | 64.1 | 58.3 | 58.8 | 57.5 | 59.7 |
| 4.2 PERF | 150 % | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |
| 3.2 OPTI | | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |
| 2.2 Rule | | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |

*Table 5.6. Percentage of demanded energy delivered with the different methods with storage and generation*

| Method | Grid Cap | Dataset 1. | Dataset 2. | Dataset 3. | Dataset 4. | Mean values all datasets |
|---|---|---|---|---|---|---|
| 4.3 PERF | 100 % | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |
| 3.3 OPTI | | 100.0 | 99.1 | 98.7 | 99.7 | 99.4 |
| 2.3 Rule | | 88.4 | 95.0 | 93.1 | 96.6 | 93.3 |
| 4.3 PERF | 50 % | 74.6 | 64.4 | 63.1 | 62.4 | 66.1 |
| 3.3 OPTI | | 74.6 | 64.4 | 63.1 | 62.4 | 66.1 |
| 2.3 Rule | | 73.9 | 62.5 | 63.1 | 62.4 | 65.5 |
| 4.3 PERF | 150 % | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |
| 3.3 OPTI | | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |
| 2.3 Rule | | 99.3 | 100.0 | 100.0 | 100.0 | 99.8 |

*Table 5.7. Minimum capacity for the different methods without storage or generation*

| Dataset | 1 | 2 | 3 | 4 | Mean |
|---|---|---|---|---|---|
| 1.1 DUMB | 51.7 | 59.1 | 80 | 59.0 | 62.5 |
| 2.1 RULE | 25.9 | 50.0 | 69.1 | 45.3 | 47.6 |
| 3.1 OPTI | 18.2 | 42.1 | 47.0 | 36.3 | 35.9 |
| 4.1 PERF | 17.6 | 41.7 | 46.7 | 34.9 | 35.2 |

*Table 5.8. Minimum capacity for the different methods and storage*

| Dataset | 1 | 2 | 3 | 4 | Mean |
|---|---|---|---|---|---|
| 1.1 DUMB | 28.3 | 47.1 | 59.0 | 31.7 | 41.5 |
| 2.1 RULE | 18.6 | 41.7 | 49.5 | 29.9 | 34.9 |
| 3.1 OPTI | 13.2 | 36.7 | 41.1 | 28.9 | 30.0 |
| 4.1 PERF | 12.9 | 35.9 | 40.3 | 28.6 | 29.4 |

*Table 5.9. Minimum capacity for the different methods and storage and generation*

| Dataset | 1 | 2 | 3 | 4 | Mean |
|---|---|---|---|---|---|
| 1.3 DUMB | 26.8 | 42.8 | 54.3 | 27.1 | 37.8 |
| 2.3 RULE | 14.3 | 37.1 | 45.5 | 25.4 | 30.6 |
| 3.3 OPTI | 9.1 | 32.0 | 36.7 | 24.9 | 25.7 |
| 4.3 PERF | 9.1 | 31.6 | 35.8 | 24.7 | 25.3 |

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