Can demand response help reduce future distribution grid investments?

An economic study of peak shaving in the Norwegian distribution grid: SEMIAH pilot in Engene, Sørlandet (Southern Norway)

Jonathan Wood
Stefan Funk

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Program: MSc in Economics and Business Administration
Profile: Energy, Natural Resources and the Environment
Supervisors: Mette Bjørndal and Endre Bjørndal

Norwegian School of Economics
Centre of Energy, Natural Resources and the Environment

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Abstract

Steady increases in the number of new electronic devices and electrification of existing technologies, such as electric vehicles, are creating new challenges in the electrical grid. Electrification creates a higher demand for electricity, thus the volume transmitted via the grid becomes larger and consumption peaks tend to increase. In addition, increasing the energy efficiency of electronic devices often results in a higher nominal power. Consequently, the shape of the load curve changes from a low and steady line to high and short peaks, for example with an instant water heater versus a standard boiler. On the supply side, increasing use of intermittent renewable sources is shifting generation from a continuous and predictable pattern to a more volatile and unforeseeable one.

All the above developments increase the requirement for more capacity on the grid. One peak hour per year decides on the grid investments for many years. Thanks to the simultaneous digitalisation of power systems and metering, new markets and business opportunities arise. One is demand response, where demand reacts to certain signals and the flexibility gained is exploited for different purposes. For example, can household devices react to reduce the peak consumption of a certain distribution grid area. Particularly in Norway, capacity in distribution grids is becoming scarce and large investments are due.

This paper investigates the question of whether by controlling household devices it is possible to reduce peak loads in the distribution grid and whether the process is economically feasible. The paper is based on a pilot in Engene in southern Norway, through the European Union funded research project SEMIAH. The examination of flexibility is achieved through the control of hot water boilers. To set up a simulation framework for a flexibility market, we studied in-depth the Norwegian electricity market, the load patterns of the transformer in Engene and the power consumption behaviour of the pilot households.

The results show that boiler flexibility can be well used to shave peaks. Optimising the household boiler consumption against market prices was less lucrative. The profitability of a demand response technology was identified as the main challenge. If business models using household flexibility will become economically feasible, it will depend a great deal on the type of devices included in the demand response system, the information technology used and the development of future power markets. Technology is evolving fast however and many service companies are focusing on the topic. Thus, implementation of peak shaving and other household flexibility concepts are likely to become a reality soon.

Abbreviations

A	Annum
AEN	Agder Energi Nett
BRP	Balance Responsible Party
CAPEX	Capital Expenditures
CET	Central European Time
CPP	Critical Peak Pricing
DR	Demand Response
DRES	Distributed Renewable Energy Sources
DSO	Distribution System Operator
ESCo	Energy Service Company
EU	European Union
EUR	Euro
FoK	Fill-or-Kill
GSM	Global System for Mobile
IoC	Immediate-or-Cancel
IQR	Interquartile Range
kW	kilo Watt
kWh	kilo Watt hours
MGA	Meter Grid Area
MIP	Mixed Integer Program
MW	Mega Watt
MWh	Mega Watt hours
NOK	Norwegian Krone
NVE	Norwegian Water Resources and Energy Directorate (translated)
OPEX	Operational Expenditures
PDC	Price Duration Curve
PTR	Peak Time Rebate
RES	Renewable Energy Sources
RKOM	Reserve Option Market (translated)
RTP	Real Time Pricing
SEDC	Smart Energy Demand Coalition
SEMIAH	Scalable Energy Management Infrastructure for Aggregation of Households
ToU	Time-of-Use
TSO	Transmission System Operator
TWh	Terra Watt hours

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1. Introduction

The instantaneous nature of electricity has always provided significant challenges for all parties involved in generating, transmitting, distributing and consuming power. Historically, a typical electricity system would be characterised by large-scale, centralised power plants providing huge quantities of electricity that are transmitted and distributed to the furthest parts of a country. As living standards increase and more technology is introduced, the demand for electricity would increase. More power plants and more infrastructure, such as cables and transformers, with higher power capacities would need to be built. In recent years, with the increasing availability of new technologies, underlined with a goal of decreasing carbon emissions across the electricity system, both the supply and demand landscapes have changed dramatically and infrastructure planning is therefore evolving.

Particularly in the EU, where climate goals are high on the political agenda, new renewable energy sources (RES), such as wind turbines and solar panels, are being connected to the grid in various sizes and at various points on the transmission and distribution chain. Even in Norway, where virtually emission-free hydropower accounts for 96% of total electricity generated [1], you can still find utility scale wind farms and households connecting solar panels to their rooftops. The intermittent nature of RES, compiled with their unconventional connection points and requirements for two-way movement of electricity, provide new challenges for grid operators. On the demand side, consumers continue to use more electricity year-on-year and, more crucially for grid operators, still have a tendency to demand electricity at certain peak periods. An increase in the use of high powered items such as electric vehicles will only increase this problem. Grid infrastructure is built purely to support the highest level of electricity demanded at any one time. If consumer demand starts to peak beyond unplanned levels, grid operators typically need to make multi-million euro investments into new infrastructure to support this increase.

One solution to these problems is to activate the demand side, known as 'Demand Response' (DR), in order to be more flexible with when the electricity is consumed. For intermittent RES, this allows the demand to better match with the supply, as consumers can be encouraged to use electricity when the wind is blowing and the sun is shining. For the grid operator, particularly the Distribution System Operators (DSO), trying to avoid ever increasing peaks in demand, the consumer can be encouraged to use electricity outside of the critical peak periods. If the encouragement is effective enough, peaks can be reduced sufficiently so that no new infrastructure is needed, at least in the mid-term, potentially saving the grid operator a considerable amount of money. It is with this second problem that our thesis is based and therefore the question we pose: can demand response help reduce future distribution grid investments?

DR as a concept was established several decades ago and for a number of years has been implemented on a larger scale with heavier consumers such as power intensive factories, where it is easier to reduce or increase demand, for example by turning on and off industrial processes. With the huge increase of installed capacity of intermittent renewable generation, DR has become a central topic to the future of electricity markets. At the same time, network planners have seen an opportunity to use DR to more efficiently manage their grid and reduce peak demand.

Since the interest and need for DR has grown, flexible businesses alone may not provide sufficient resources with which to play with. Residential consumers will therefore need to be included. A large number of households aggregated into one controllable unit of power can provide excellent flexibility to a distribution grid system. Within each household various appliances, such a hot water boiler, can be controlled using automated software that responds to signals of when and when not to consume electricity. The control of these household appliances could be given to the DSO, who would have the best knowledge of when the peak periods could occur, or it could be given to another party where the DSO's peak shaving priority is one of many objectives in a wider optimisation of the aggregated household load. One such party, often termed an 'Aggregator', will look to optimise the households' consumption to extract as much financial value from this flexibility as possible, through optimising against all possible revenue sources – day-ahead, intraday and ancillary service markets for electricity or perhaps new markets for flexibility. In return, the household is likely to request some form of incentive, financial or otherwise, in return for offering their flexibility. This thesis will discuss how, in the Norwegian electricity market, it would be possible to implement such a DR scheme, how successful this could be, what challenges would be faced and whether this would be a cost-effectively tool for a DSO to reduce their future grid investments.

This thesis has been written around a pilot study of 100 households each of which contain a hot water boiler that can be remotely controlled using DR software. The pilot and this thesis are part of a European research project named SEMIAH – Scalable Energy Management Infrastructure for Aggregation of Households – with the aim of making technological, scientific and commercial breakthroughs towards implementation of DR in households. The pilot is located in Engene, in the Sørlandet region of southern Norway. The location was chosen by the representative DSO for that area – Agder Energi Nett (AEN) – who are also partners in SEMIAH. AEN are due to upgrade a transformer in this region and would like to explore the possibility of using DR to avoid or delay this investment. Another partner of SEMIAH, software company Misurio AG, has assisted us in developing the model for optimising the households and some of the content of this thesis is therefore intellectual property of Misurio AG.

Previous literature has tended to focus on only one aspect of the problem, for example just looking at the size of the peak shaving possible or just looking at the theoretical market model for flexibility. The strength of this thesis lies in the consolidation of many aspects: evaluating the challenges facing DR schemes, assessing the magnitude of peak shaving possible from a particular appliance, presenting an optimisation model with which this can be exploited and translating these results into potential investment cost savings for a DSO.

Chapter 2 of this thesis will discuss the details of the Norwegian power market and how DR fits into this picture. Understanding the fundamentals of the Norwegian power market is essential in constructing a flexibility market and how a future aggregator can optimise their procurement costs of electricity. Chapter 3 will discuss the principles of peak shaving and DR, and review previous evidence on the effectiveness of DR in reducing peak load and what the potential investment cost savings are for DSOs. Chapter 4 will discuss the expected future changes in the Norwegian power system and how this will affect the success of DR. Chapter 5 will introduce the SEMIAH pilot study, discuss in detail the problem faced by AEN and analyse the household data we have available in our project. Chapter 6 will present the results of two optimisations where either the DSO or an ‘Aggregator’ controls the households and enacts the DR, under various constraints to ensure a robust outcome. Chapter 7 evaluates these results in a real-world context. Chapter 8 concludes the thesis.

2. The Norwegian Power Market

In this chapter, we give a detailed overview of the Norwegian power market. This includes financial markets, ancillary services, balancing power pricing and grid tariffs. The basic understanding of the power market is essential to understanding the opportunities and challenges of DR. The exploitation of household flexibility is a concept that requires a wide understanding of the mechanisms of power systems and markets. Further, the analysis will serve us when specifying and modelling the optimisation to quantify the benefits of DR in chapter 6. While some elements are explained to understand our later models, other market characteristics may be discussed simply to make clear why they cannot be considered.

The Energy Act of Norway of 1990 allowed Norway to liberalise its electricity market and become one of the few countries pioneering in this field. Consequently, Norwegian consumers could choose their electricity supplier freely. After the other Nordic countries followed, the power exchange NordPool was founded in 1996. As the first power exchange in the world, NordPool implemented cross-border trading. Today, NordPool consists of the member countries Norway, Sweden, Finland, Denmark, Estonia, Lithuania and Latvia. The Nordic power market is integrated into the European market through interconnectors with the neighbouring countries [2].[1] In 2015, the volume traded on NordPool equalled 93% of total Nordic power consumption, which shows the significance of the wholesale market [1].

The Norwegian power market differs from those in central Europe. Thanks to massive water reserves, Norway can produce 96% of its yearly electricity volume of approximately 130 TWh from hydropower. A large share of the production is flexible and storage possibilities of up to 85 TWh exist [1]. Consequently, electricity price volatility between days is relatively low. Imbalances can be handled by Norway's flexible power generation. On the contrary, seasonal price volatility is relatively high due to changes of the hydrological conditions, e.g. snow melting periods or periods with extremely high participation. Besides the influence on price, the hydrological conditions also impact the country's power balance. While in the summer lots of water

[1] Currently interconnectors exist to Germany, Poland, the Netherlands, Estonia and Russia.

is available and Norway is mostly exporting power, in the winter water is mor scarce and Norway becomes a net importer. Overall the country's trading balance with power is usually positive and net export in the last five years was 11.3 TWh [1].

The transmission of electricity in Norway is divided into three different types of grids; transmission grid, regional distribution grid and local distribution grid. The different grid levels operate under different voltage levels to minimise transportation losses. The voltage level is between 420 and 300 kV in the transmission grid, between 132 and 33 kV in the regional distribution grid and between 22 and 0.230 kV in the local distribution grid. While the transmission grid is 90% owned by the Transmission System Operator (TSO) Statnett, the two distribution grid types are owned by many different DSOs [3].

The Norwegian power market trading scheme is very similar to that of other European countries. Each entity that wishes to trade power needs to be registered as a Balance Responsible Party (BRP). BRPs are always supposed to balance consumption and production, otherwise they are penalised. This is due to electricity needing to be consumed instantly, otherwise the grid becomes unstable and an outage is risked [4].

Long-term liabilities and hedging are taken care of via the financial market for derivatives. Derivatives for Norwegian power are usually processed bilaterally or on the NASDAQ OMX exchange. Most of the physical short-term demand and supply in Norway is traded on the day-ahead market, which is a daily auction for the following day's power. All the purchases are based on generation and consumption forecasts that are updated as soon as there is new information available. Due to forecast errors and other uncertainties, there will almost always be a discrepancy between what was sold/purchased on the day-ahead market and what needs to be produced/consumed when the time comes. This mismatch can be corrected as much as possible on the intraday market until one hour before delivery[2]. Any further volumes are traded over-the-counter. Balancing mechanisms and ancillary services compensate for differences of supply and demand and are arranged by Statnett [5].

The Energy Act defines the regulatory framework of the electricity supply in Norway. This legislation is issued by the Norwegian government. The Norwegian Water Resources and Energy Directorate (NVE)[3] has the power over regulations in the essential areas, in accordance with the Energy Act [5].

[2] Between the German TSO areas, gate closure time is 20 minutes before delivery time.

[3] Norges vassdrags- og energidirektorat (NVE) in Norwegian

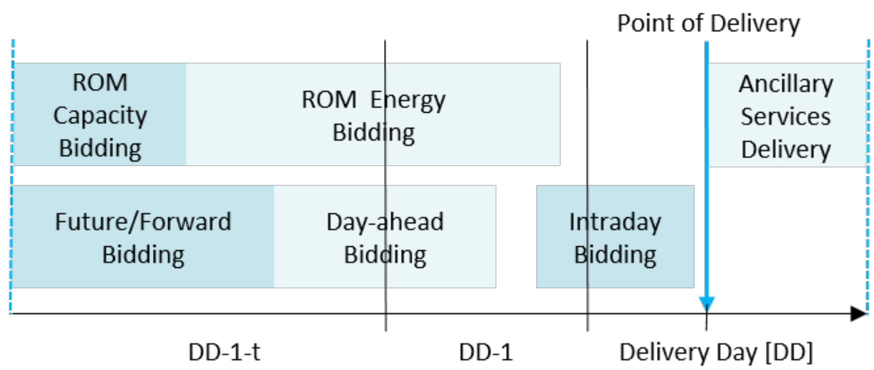

Figure 2-1: Bidding scheme for the Norwegian Power Market.

2.1 Day-ahead Market

The day-ahead or spot market is the main platform for trading power and is called Elspot. In the Nordics, this is arranged by NordPool, as with the intraday and financial markets. The day-ahead market is based on an auction for the delivery of electricity on the following day. Bids can be submitted until 12:00 CET and the results will be published at 12:42 or later. Consequently, the power on the day-ahead market is traded between 12 and 36 hours in advance [6]. For bidding, different order types are available that help to replicate the bidding parties' different needs. Currently, there exist four different order types at Elspot: single hourly orders, block orders, exclusive group orders and flexible orders. The detailed characteristics of the different order types can be found in [7].

The so-called system price is calculated on a predefined algorithm that simulates a market cross between the aggregated supply and demand curves of all submitted bids. This system price is based on the principle of no capacity constraints within and between countries [6]. However, this does not reflect the reality and bottlenecks between countries and different price areas within countries must be considered. The subdivision of the grid in various regions reflects those bottlenecks at least partially. Norway is divided into five price areas – NO1, NO2, NO3, NO4 and NO5. In each price area, bids are aggregated to a supply and demand curve. The intersection of the two will define the area price in the same manner as was done for the system price. Whenever there will be a surplus and a deficit in one area, the price will be raised in the area with the deficit and lowered in the area with the surplus, until the congestion between the two is utilised maximally. Hence, the system price never is the same as the area prices unless none of the capacity constraints of the TSO are binding [7].

2.2 Intraday Market

As with the day-ahead market, the intraday market named Elbas is managed by NordPool. The intraday market works as a balancing market to minimise the mismatch between day-ahead market results and actual power consumption due to forecast errors or unforeseen events. The market follows a pay-as-bid principle and basically works like a regular stock exchange. Elbas is open 24 hours a day, 7 days a week, 365 days a year, so electricity of the actual day can always be traded at any time.

The intraday market also uses several different order types – limit orders, block orders and iceberg orders. Limit orders are either buy or sell orders than can be executed at a set price or lower if it is a buy order, or higher if a sell order. The existing products are for delivery of 15 minutes, 30 minutes or one hour. Limit orders can be carried out partially. On Elbas, a block order consists of consecutive hourly orders and are also 'all-or-nothing'. The idea behind iceberg orders is to hide the actual volume of a large bid by splitting up into smaller shares. The first share of the bid will appear on the market and the next one will be released when the previous one has been accepted. The different shares can be priced differently.

Elbas also offers the possibility for constraints on orders, such as Fill-or-Kill (FoK) and Immediate-or-Cancel (IoC). If FoK is selected for an order, the bid will either be matched immediately when the entire volume has matched or cancelled otherwise. If an order is marked as IoC, as much of the volume as possible will be matched immediately and the rest will be cancelled.

2.3 Ancillary Services in Norway

One of the TSO's most important responsibilities is security of supply, which is a consequence of the physical characteristics of electricity. Unlike other energy sources, electricity produced must always be consumed instantly.[4] If the grid is not balanced at any time, a blackout can occur. Even though electricity markets are designed to balance consumption and production at any given time by itself, in practice they

[4] Based on today's technology, some storage possibilities exist when electricity is converted into other energy carriers, such as hydrogen, chemical batteries or water in the form of pumped storage. All storage options have significant disadvantages due to limited capacity and high efficiency losses. As of now, the role of storage is considered minor. However, it is likely that innovation in storage technologies and decentralised storage will change this in the future.

cannot usually succeed. Abrupt events and the impossibility of perfectly forecasting electricity demand will always leave the TSO with a certain mismatch. To avoid outages, the TSO manages ancillary services to balance the grid. Those services are usually open for any power producer that can fulfil the technical requirements needed to participate. In Norway, all ancillary services are also open for demand side units.

	Frequency Controlled Normal Operation Reserve	Frequency Controlled Disturbance Reserve	Secondary Control Reserve	Reserve Option Market High Quality (RKOM-H)	Reserve Option Market Low Quality (RKOM-B)
Product	Symmetrical control power bands	Positive control power bands	Asymmetrical control power bands	Positive control power bands	Positive control power bands, with duration limits and resting time
Tender Periods	Weekly Daily	Weekly Daily	Weekly	Weekly Seasonal	Weekly Seasonal
Lot Sizes	+/- 0.1 HZ	+/- 0.1 HZ	Min 5 MW Max 35 MW	Min 10 MW (Not ordinary bids min 1 MW)	Min 10 MW (Not ordinary bids min 1 MW)
Compensation	Marginal costs as service price of the power needed to increase/reduce the frequency	Marginal costs as service price of the power needed to increase/reduce the frequency	Marginal price as service price Nordic upward/ downward regulating price as working price	Marginal costs as service price and regulating price as working price	If quality does not matter, the same price as high quality, if quality does matter adjusted lower price for low quality
Reaction Time	Immediate	Immediate	120-210 seconds	15 minutes	15 minutes
Pooling	Norwegian Market	Norwegian Market	Is allowed	Is allowed	Is allowed
Activation	Decentralised (Frequency control)	Decentralised (Frequency control)	Decentralised (Frequency control)	Signal from grid controller	Manually
Volume	± 210 MW	+ 350 MW	Information not available from Statnett	1700 MW (Total regulating power high and low quality)	

Table 2-1: Overview of the technical specifications of the available ancillary services in Norway [8–13].

The principle of ancillary services is rather simple. If there is more electricity produced than consumed, the TSO will ask some of the participating production units/consumption units to decrease their production/increase their consumption and vice versa. The controllable units are often required to react immediately, which is not feasible for all. Different ramping up and down characteristics allow only a few controllable units to adjust in almost real-time. Hence, ancillary services are divided into different stages that will slowly phase out imbalances. In Europe, there are usually three different stages of ancillary services; primary control reserve, secondary control reserve and tertiary control reserve. Primary control reserve is often called frequency control since the controllable units participating automatically measure the frequency of the grid and ramp up or down production immediately. After approximately 30 seconds, primary control reserves are phased out and secondary control reserves are activated. On the secondary level, the TSO usually sends a signal to the controllable unit that will be activated automatically. After 15 minutes, tertiary control reserves, the last level of balancing services, is activated. The activation often happens manually. The TSO sends out an email or a call to the participant. An overview about the ancillary services in Norway is provided in Table 2-1.

2.3.1 The Norwegian Tertiary Control Reserve Market

The Reserve Option Market (RKOM)[5] is a capacity market and compensates its participants to hold back a certain amount of up regulating (positive) power for a specified period. Each participant submits a price that reflects their willingness to provide positive reserve capacity of at least 10 MW for either a specific week or a whole season in the located bidding area. The bids are marginally priced. Thus, the cheapest bids will be accepted and everybody receives the price of the last accepted bid – the marginal bid. Each participant that gets accepted in the option market is obligated to submit a bid into the balancing energy market (RKM)[6] for activating their hold back reserve capacity by 9.30 pm the day before [13].

In the balancing energy market, the cheapest bidders of both up and down regulating power will be activated in case of system imbalance. The price is calculated after each hour of operation has passed. All the data is collected and the price for regulating energy is calculated. As with the option market, marginal pricing is applied for the balancing energy market and everybody receives the price of the most expensive bid

[5] Regulerkraftopsjonsmarkedet (RKOM) in Norwegian

[6] Regulerkraftmarkedet (RKM) in Norwegian

accepted. The price for up regulation is never below the equivalent spot price and always higher than the according fee for down regulation [12].

For both seasonal and weekly reserve capacity, high and low quality bids can be submitted – RKOM-H and RKOM-B respectively, as outlined in Table 2-1. High quality products must be available during the whole period the bid is submitted for (week/season). Low quality products provide reserve power only during a limited amount of time. It can be specified for how long a certain service is available (minimum one hour) and how much recreation time is needed until the capacity is available again (maximum eight hours). In case the TSO does not skip certain bids in the merit order curve due to limitations in the quality, high and low quality reserve capacity will receive the same remuneration. If the TSO must skip some of the bids due to the limitation in quality, the price for low quality reserve power is determined as follows:

$$Option\ Premium\ = Duration\ Factor \times Recreation\ Factor \times Bid\ Volume \times Marginal\ Price$$

The duration and recreation factors are multiplied by the marginal price and the volume of the bid. The shorter the time capacity can be provided for and the longer the break for the unit to recover, the lower the capacity payment will be, see Table 2-2. Consequently, the price for low quality reserve capacity is always the same or lower than for high quality [13].

Duration	**Duration > 4h**	**4h**	**3h**	**2h**	**1h**
DF	1	0.98	0.95	0.90	0.8

Recreation time	**No resting time**	**1h or 2h**	**3h or 4h**	**5h or 6h**	**7h or 8h**
RF	1	0.98	0.95	0.90	0.8

Table 2-2: Duration and recreation factors for the calculation of the option premium, from [13].

If a bid in the balancing energy market is activated and the dedicated participant is not able to provide the requested energy, he must pay a penalty. The penalty is dependent on how much energy could not be delivered, the quality of the bid and type of unit. The penalty is calculated in the following way [13]:

$$Penalty = A \times Deviation\ Price \times Missing\ Energy\ Volume$$

Where A is the deviation factor. It takes on the value of 25 for bids into the high-quality reserve market. For the bids into low quality market the value is set to 25 for production units and to 2 for consumption units. The deviation price is a volume weighted price based on options for weekly, seasonal and special purchases of the actual product.

2.4 Balancing Groups and Balancing Energy

Every entity that would like to take part in the wholesale market must enter a balance settlement agreement with Statnett. Each entity authorised to trade then represents a Balance Responsible Party (BRP). The reason for this is once again the need for the electricity grid to always be in balance. BRPs are required to have their positive and negative power flows balanced.[7] Their power balance must be reported periodically to the TSO so imbalances can be calculated and billed appropriately.

The Nordic imbalance settlement is based on the harmonised Nordic model, which was implemented in all Nordic[8] countries in 2009 [4]. The model is based on production and consumption imbalance. Both types of imbalances are derived and priced differently. The production imbalance is the difference between the metered production and the planned production, plus production imbalance adjustments (ancillary services provided) – see below equation. Consumption imbalance is calculated as the sum of consumption, planned production, trades, consumption imbalance adjustments and Metering Grid Area (MGA)[9] imbalances. It must be noted that the imbalance adjustment elements can have a positive or negative sign.

$$\begin{aligned} &\mathit{Production\ Imbalance\ Power} \\ &\qquad = \mathit{Producion} \ - \mathit{Planned\ Production} + \mathit{Production\ Imbalance\ Adjustement} \end{aligned}$$

$$\begin{aligned} &\mathit{Consumption\ Imbalance\ Power} \\ &\qquad = \mathit{Consumption} \ + \ \mathit{Planned\ Production} \ + \mathit{Trade} \\ &\qquad + \mathit{Consumption\ Imbalance\ Adjustement} + \mathit{MGA\ Imbalance\ Adjustement} \end{aligned}$$

[7] As an example, all the power he consumes needs to be covered by trades on NordPool Elspot.

[8] Sweden, Norway and Finland

[9] MGA is defined as the area in the TSO's grid where a BRP operates. In a Metering Grid Area, consumption and production are metered. The area can contain consumers and producers or just one of them. They are used to determine the balance of production and consumption [4].

	Up-regulation hours	Down-regulation hours	Hours with no direction
Two price model for production imbalances			
Negative production imbalance (BRP buys)	Up-regulation price	Elspot	Elspot
Positive production imbalance (BRP sells)	Elspot	Down-regulation price	Elspot
One price model for consumption imbalances			
Negative consumption imbalance (BRP buys)	Up-regulation price	Down-regulation price	Elspot
Positive consumption imbalance (BRP sells)	Up-regulation price	Down-regulation price	Elspot

Table 2-3: Imbalance prices for BRP in the Nordics, from [4].

The pricing of the production imbalance is based on a two-price model. The price is always the less favourable of the corresponding area spot price from Elspot and the imbalance price. The imbalance price depends on the direction of the regulation in the specific hour. Contrarily, the consumption imbalance price is based on a one price model and thus, always equals the imbalance price of the area – see Table 2-3.

2.5 Transmission & Regional Grid Tariffs

Whenever a producer or consumer is connected to the transmission grid or a regional grid that belongs to Statnett, they have to pay a fee for the usage of the network [14]. In Norway, this fee has two components: the energy component (Energiledd) and the capacity component (Faste ledd). The energy component reflects the costs caused by the amount of energy fed into the grid or consumed from the grid. The total energy costs are the product of the spot price in the particular area, the marginal loss rate and the total amount of energy consumed/produced. The marginal loss rate is defined and published weekly by Statnett on their homepage. There is a separate loss rate for day (06:00 – 22:00) and night (22:00 – 06:00). The marginal loss rate is symmetric for each connection point and has a cap at plus and minus 15%.

$$Energy\ costs\ (NOK) = \text{NOR Area Price}\left({}^{NOK}/_{MWh}\right) \times Marginal\ loss\ rate \times Energy\ (MWh)$$

The capacity component distinguishes between producers and three different kinds of consumers. Since this work is focusing on the demand side, we will not go into further details on producers. The three different types of consumers are flexible consumers, large consumers and other consumers. Flexible consumers have special agreements that allow Statnett to disconnect them from the grid for a specified amount of time. Large consumers have a minimum of 15 MW power consumption in at least 5000 hours of the year. Other consumers are everybody that does not qualify for the two previous categories. Since DSOs will most likely fall into large consumers from this tariff perspective, we look at them in more detail.

The capacity costs for large consumers are calculated by the average consumption during the peak hours of the last five years, times the 'k-factor' and the individual tariff. The peak hour is determined as a global maximum for the north, west and south region for each year. For calculating the year 2017, the average consumption from 2012 to 2016 applies. The k-factor corrects for production in connection points that are exposed to both consumption and production. The k-factor is calculated as the sum of all consumer's average consumption at the connection during the peak load hour of the five previous years, over the total available production capacity at the connection point plus the same sum of all consumer's average consumption over the last five years. The values for k will be between 0.5 and 1. For any value below 0.5, k is automatically set to 0.5. The available production capacity for the winter depends on the production technology. For hydropower, the capacity is defined as the highest amount that can be produced during a continuous 6 hours in the period with the highest consumption in winter. For wind power, 50% of the installed capacity is considered and 100% for thermal power.

$$power\ costs\ (NOK/A)\ = avg.\ peak\ hour\ outtake\ (MW) \times k \times \left[cons.tariff - ind.\ reduction\right]$$

$$k = \frac{F_s^{tot}}{P_f + F_s^{tot}} \qquad If\ \ k \leq 0.5\,, \qquad k = 0.5$$

The individual tariff is calculated as the difference between Statnett's consumption tariff and an individual reduction up to 90%. The individual reduction depends on the peak hour consumption, the variation in consumption and the consumption during summer. The lower the peak hour consumption, the lower variation over the whole year and the higher consumption during the summer relative to the rest of the year, the larger is the reduction on the individual tariff. In other words, any effort in helping to avoid peaks and congestion in the transmission grid is rewarded.

2.6 Distribution Grid Retail Tariffs

The structure of distribution grid tariffs is highly relevant for research on DR and is strongly linked to possible business models. Tariffs can influence the end consumer's electricity consumption behaviour in different ways. Sending the wrong signals and giving undesired incentives to end consumers must be strictly avoided. On the contrary, sending out the right signals can help DR solutions solve market inefficiency problems and allow for new market based solutions.

The following sections will outline the basic principles of grid tariffs and explain different ways of designing them. In addition, the current and future situation in Europe and Norway will be explained.

2.6.1 Principles of Distribution Network Pricing

The electrical grid is typically a natural monopoly, such as the gas pipeline network or railways in some countries. Natural monopolies usually appear when extremely high fixed costs are required to enter a certain market, such as investments into infrastructure. The effects of economies of scale are significant. Allowing more than one market player would lead to a duplication of infrastructure. That is usually a waste of resources and makes the market inefficient.

To avoid the abuse of market power, natural monopolies need to be regulated [15]. Consequently, the distribution grid is a regulated business field. Eurelectric [16] defines the typical DSO tasks as planning, development, connection and operation of distribution grid systems, such as the facilitation of existing retail market processes, metering and guaranteeing reliability and quality. Grid tariffs are supposed to cover the costs that arise from those activities while reflecting the actual structure of fixed and variable costs. The main drivers for those costs usually are topology of the network and peak capacity [17].

Grid tariffs are determined in two steps: the identification of a DSO's billable costs to the end consumer – operating expenditure (OPEX) and capital expenditure (CAPEX)

– and the definition of the actual tariff scheme. While the first step decides on the signals the grid tariff conveys to the DSO for increasing their own efficiency, the second step decides on the signals sent out to the end consumer [16].

Costs the DSO can allocate to CAPEX are typically investments into assets that are required to provide all required grid services – such as substations, overhead lines or underground cables. OPEX includes customer services, overhead costs, system services and maintenance and network losses. Since tariffs should reflect the adequate cost structure, CAPEX should be covered by the fixed component of the grid tariff and OPEX should be covered by the variable component of the tariff. In addition to cost structure reflectiveness, tariffs should be economically efficient so that signals sent to DSOs and their customers are welfare maximising, fully recover the network costs and fairly allocate them to the consumers of the capacity. Hence, the difficulty of tariff design lies in balancing all the mentioned targets while not constraining but supporting progress in DR and energy efficiency [17]. It should be noted that even if human consumption behaviour does not change, the right structure of tariffs can still provide incentives for automatic DR.

2.6.2 Types of Grid Tariffs

The handling and design of grid tariffs differ considerably among countries. The different ways grid tariffs can be structured are described below. There are two different ways of how end consumers are invoiced for the grid tariff. The first is when the energy and grid component are handled separately. The supplier is responsible for sending the end consumer the bill for the energy component and the DSO is responsible for sending the end consumer the grid component. The second possibility is that only the energy supplier is in direct contact with the end consumer and sends one bill to them. On the bill the supplier states the cost for energy and for the grid separately or combines them into one price for electricity. The first system is currently used in Norway but in future will be switched to the second model [18]. Please be aware that the billing system does not affect the type of tariff used. The only difference is the entity dealing with the customer relationship. In countries where the energy supplier only is in contact with the consumer and all components of actual electricity costs (tax, energy, capacity and subsidies) are reflected in one single price, many people will not even realise that there is such a thing as a grid component.

The way grid tariffs are designed will determine the signals sent to the end consumer and can provide incentives to support a certain behaviour. Therefore, tariffs should be defined carefully, so they comply with the targets outlined in the previous section.

First, there are two fundamental drivers for grid tariffs: volume and capacity. Volumetric tariffs are based on the energy that is delivered to an end consumer or fed into the grid (EUR/kWh). Stated differently, the end consumer pays for electricity consumed or produced. As an analogy with water, this would mean a household pays for the total amount of water he has used over a certain period. Volumetric tariffs do not consider when the electricity was consumed or fed-in. All that matters are the total volume consumed or fed in over time.

Capacity based pricing depends on the maximum instantaneous power an end consumer uses on the network they are connected to (EUR/kW). The end consumer pays for the maximum capacity of their connection to the grid. Comparing with water, this would mean a household would pay for the size of the pipe that is connected to their house. The total amount of water used is irrelevant and only the maximum instantaneous consumption affects the costs. Fees for capacity could also be recovered through a fixed charge. Large end consumers usually pay a fixed fee for their connection to the grid in addition to other variable charges. In addition to a volumetric or a capacity based tariffs, a general fixed fee can be used. In some cases, such as currently in Norway, the capacity element of a distribution tariff can be charged within this fixed fee.

For both volumetric and capacity based grid tariffs, different types of pricing exist. The most commonly used are as follows [17].

Time-of-Use Pricing

Time-of-Use (ToU) tariffs are predefined, fixed tariffs for a particular time interval. For instance, during times of high demand, a high tariff would apply and during times of low demand, a low tariff would apply. Common are night and day tariffs, where the night tariff would be cheaper. The aim is to incentivise the shifting of load from peak hours to off-peak hours. ToU tariffs build on historical data on grid usage and are defined before the billing period starts.[10]

[10] Often they are determined at the beginning of each year.

Critical Peak Pricing

Critical Peak Pricing (CPP) is like ToU pricing, in the sense that tariffs are higher during a certain period. In contrary to ToU, CPP applies only for some critical hours and is announced usually one or two days ahead. The exact duration for CPP and whether different peak periods over the day are defined depends on the tariff design. CPP is mostly used for higher levels of grid capacity. A critical period can be seen as a movable ToU interval.

Dynamic Grid Pricing

Dynamic grid pricing refers to short-term announcement of grid tariffs, e.g. one hour before delivery. The idea of the concept is to regulate congestion due to volatile electricity demand.

For DSOs it is possible to apply either a volumetric based grid tariff, a capacity based grid tariff or a combination of the two. Hence, grid tariffs can contain different components. Their eventual design depends on regulations, typology and the weighting of the different objectives explained in the previous section. The trend is toward more marginally priced designed tariffs so that the people causing the highest need for capacity also pay the most. This results in more capacity based tariffs and stimulates the business case for DR.

2.6.3 Current Challenges in the Design of Distribution Grid Tariffs

While the market is changing, in most European countries the regulation of current distribution grid tariffs still corresponds with the traditional characteristics of a centralised electricity market. The traditional design does not consider much production connected to the distribution grid or bi-directional power flow [19]. Due to a more decentralised production and consumption of electricity, new approaches for the tariffing of power and the pricing of electricity in the retail market have appeared. In a recent paper on network tariffs, Eurelectric [17] identified important challenges and addressed them accordingly. One issue DSOs are currently facing is the decrease in distributed electricity volume due to the increasing number of ‘prosumers’ – consumers who both consume and produce – and progresses in energy efficiency, resulting in lower revenues for the DSOs. Capacity based tariffs in combination with further mechanisms that allow a timely recovery of tariff revenues could mitigate diminishing DSO incomes.

Another issue Eurelectric identifies as being caused by the increasing number of prosumers, is the fair allocation of costs. Fair allocation of costs means that the grid should be paid according to the impact each customer has on it. Self-produced electricity does not necessarily reduce the grid investment and management costs. On the contrary, sometimes self-produced electricity can even increase the expenditures for the network, for example the setup costs in allowing bi-directional flow. Decentralised, self-producing customers usually still depend on access to the grid, especially during peak hours. Hence, tariffs should be designed in a way so they are fair and non-discriminatory. Customers with the same need of a connection to the grid should make the same payment for the service they receive [19].

Utilisation of the grid can be improved, if tariffs provide the right incentives. End consumers could change their habits and reduce peak load. Manually triggered DR has its limitations though. Studies show (see chapter 3) that the effects are usually rather marginal if the tariffs expect consumers to manually change behaviour. For example, ToU tariffs are often not capable of reducing household load by more than a few percent during a peak hour. Automatic controlled DR is able to provide much higher monetary incentives for end consumers than manually controlled [20]. Eurelectric [17] states that more capacity based grid tariffs would support DR, having for instance ToU tariffs included in the capacity component. Such a framework is ideal to give end consumers with controllable loads the opportunity to shift their load and avoid peaks during critical hours.

The end consumer is exposed to the retail price, that will have an energy, grid and tax component. Hence, the overall price signal will be a combination of different incentives related to energy efficiency and grid efficiency. The energy efficiency is driven by the energy component in the retail price. The energy signal mostly effects the consumer's overall consumption and can also, if dynamic, shift consumption in time. Even though retail prices are constructed based on all the principles mentioned, it is not unlikely for end consumers to adjust behaviour drastically in the short-term. Nevertheless, retail prices might influence long-term consumption patterns and can have an impact on decisions about investment into new devices (e.g. solar panels, EVs) [17]. A more in depth discussion on DR literature will be presented in chapter 3.

2.6.4 Current and Future Tariff Structure in Norway

In Norway, distribution grid tariffs are designed by the DSOs complying with the principles set by NVE [21]. The current regulation from NVE leaves DSOs with considerable freedom regarding the design of distribution grid tariffs. The fees for households, vacation houses and small commercial customers comprises a fixed component per year (NOK/annum) and a volumetric component (NOK/kWh). The fixed component usually accounts for around 30% of the grid tariff. Statistics Norway [22] have calculated that the total grid costs contribute approximately to one third of the total electricity costs, with one third from energy costs and one third from taxes – see Figure 2-2.

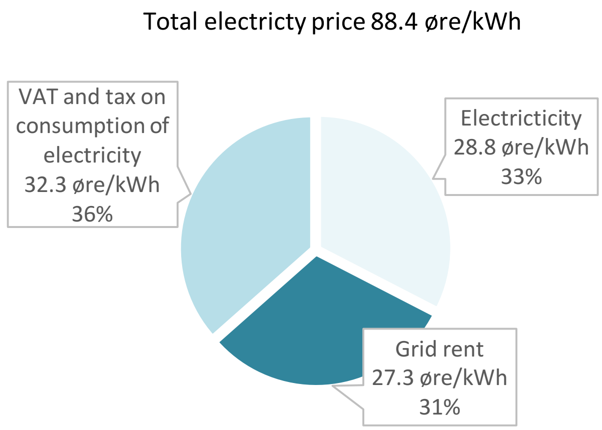

Figure 2-2: Electricity Costs for Norwegian households, from [22].

End consumers that exceed an annual consumption of 100,000 kWh or defined limit of 80 or 125 amperes, must pay an additional capacity fee (NOK/kW) as well. This capacity component depends on the maximal capacity used over a set period.

In NVE's [21] opinion, distribution grid tariffs should follow the aim of effective utilisation and development of the grid, as well as the target of a reasonable distribution of the costs incurred. Since demand for peak hour capacity is one of the main drivers for network cost, it should also be reflected in the grid tariff. At least for households, this does not apply yet. In addition, all electricity end consumers in Norway will be equipped with smart meters by January 1, 2019.[11] The new technology provides all parties involved in metering and billing processes with more precise data regarding consumers' consumption and production behaviour. This allows for more advanced electricity tariffs than just volumetric ones.

Consequently, NVE has examined the current regulation for the design of grid tariffs by public consultation. The goal was to check whether other tariff models might apply

[11] The roll out of smart meters has already started in Norway and progress depends on the DSOs. It must be completed by January 1, 2019 [83].

better with current and future electricity markets. Clearer guidelines for the DSOs on how to design grid tariffs shall be provided. To ensure the cost-by-cause principle, NVE states that a capacity component must be included in grid tariffs also for small consumers. For that purpose, NVE introduces three different tariff concepts to incorporate capacity into network tariffs.

The first concept is capacity charges based on the measured capacity used (NOK/kW). The end consumer will pay for its maximum capacity used over a certain time interval. As an alternative, NVE mentions ToU pricing that would have a similar effect (consumption smoothening), yet would be easier to communicate. With ToU pricing, consumers do not have to understand the principle of capacity tariffs but can relate to the predefined peak hours when electricity will be more expensive than during the off-peak hours.

The second concept is also based on capacity charges but refers to the installed capacity (NOK/annum or NOK/kW). The consumer pays a fixed amount every year for the capacity of the connection. The approach is not dynamic since it relates to the consumer's physical installation (i.e. capacity of their connecting line) and therefore cannot influence their consumption behaviour but it does provide a guaranteed revenue stream for the DSO.

The third concept is capacity charges, based on subscribed capacity. If load exceeds the subscribed capacity level, the consumer will be penalised or their consumption will be curtailed. At the stage of evaluation, consequences of subscribed capacity tariff models were not yet known to NVE. Hence, NVE does not intend to implement such as capacity scheme for now. The model may be still relevant for future regulation frameworks, after more experience regarding capacity tariffs, smart meters and end consumer behaviour has been gained (see Sæle et al. [23] for more detail on subscribed capacity, discussed in section 3.3.3).

NVE's focus lies on capacity charges based on measured capacity used as it is applied for today's large consumers. In addition, NVE wants to pave the way for ToU pricing as an alternative. While rolling out the smart meters, DSOs should collect the data of the installed capacity, so the physical capacity of their customer is known and can be considered for fixed pricing models. A gradual restructuring of grid tariffs should be excepted in the coming years, which particularly concerns DSOs with high energy grid fees and low fixed fees.

Another scope of NVE is the replacement of interruptible load contracts by a market for flexibility. The interruptible load contracts offer reduced tariffs to those customers that enter an agreement with their DSO to allow cutting off their consumption in the case of congestion. NVE does not intend to prohibit interruptible load contracts before a sophisticated and tested market solution for flexibility is developed. Interruptible load contracts can be useful during outages, maintenance and other operational challenges. This can lead to reduction in grid investments in a different way than flexibility markets. Hence, the two concepts could also be maintained alongside.

3. Peak Shaving

Peak shaving can be defined as reducing the electrical load of a particular system during a period of peak demand. This could be achieved through a DR system in which household heating is automatically controlled. In this example, if the heating is turned off for a certain period, to achieve the same level of comfort, it is likely the household would need to switch the heating back on after the off period. We can then consider this load as 'shifted' to another period, as opposed to 'shaved'. Figure 3-1 illustrates the two concepts of peak shaving and load shifting.

Figure 3-1: Peak Shaving vs Load Shifting, from [16].

In most instances, users demand a relatively set level of electricity over time as they always wish to heat their homes and hot water to a certain temperature, have to wash clothes at regular intervals and so on. Therefore, rather than completely shaving the peak of electricity to be never demanded again, in most instances the load will be shifted from one period to another.

In some instances, there is more focus placed on moving the load to a different specified period, as opposed to just reducing during a peak period. For example, when dealing with intermittent RES. If wind power represents a large share of a community's electricity supply, there could be a scenario where a peak in electricity demand occurs when the wind is not blowing. Some of the demand could then be shifted to when the wind is predicted to blow and when wind power can be generated. For the purposes of this thesis however, we are concentrating purely on reducing the highest peaks of electricity in the AEN network. We are therefore unconcerned with which period the load is shifted to or whether the achieved result is indeed load shifting or pure peak shaving – unless of course the shifting of load causes a secondary even higher peak. In our market simulation presented in chapter 6 however, we do place a constraint that guarantees the same household consumption each day pre- and post-optimisation, therefore the result will always be load shifting. Adverse effects such as secondary peaks will also be controlled for in the model.

As previously discussed, a main motivation for reducing load during peak periods is due to the strain that the build-up of electricity puts on the grid. Each component of any electrical grid can only handle up to a certain threshold of power. If these thresholds are exceeded when demand peaks above these values, then there is risk of damage to the infrastructure or even an outage. Having a mechanism to potentially reduce these peaks allows a grid operator to better manage system reliability and reduce costs from damage to infrastructure. In the longer term, with the increased use of electrical devices and electrification of transportation, it is expected that electricity demand will continue to rise [24], likely leading to more peaks that approach or exceed these thresholds. Historically, the typical approach of the grid operator would be to upgrade to a higher capacity component which would give more ‘room’ for these increasing loads in the future. As an alternative therefore, actively reducing demand in order shave these peaks could help to reduce long term investment costs, if such an upgrade can be avoided or delayed. Whether these long-term grid investments can be cost-effectively avoided or delayed using DR techniques is the basis of our thesis.

3.1 Potential in the Distribution Grid

As indicated above, the traditional method for distribution network planning is to make an assessment of future loads and build the required infrastructure to deal with the capacity of the highest peaks that are forecast. Extra lines and transformers or ones with higher capacity would be built to support the highest load forecast in 10-50 years’ time. This is what is known as a “fit-and-forget” strategy, in which the infrastructure is built, and the problem is forgotten for many years until a new upgrade is required.

With the advent of DR, DSOs now have the opportunity to take a different planning strategy – one in which they could forecast how they could reduce future loads using DR, and thus delay or avoid infrastructure investment, reducing their costs. In addition, with increased uncertainty around the future generation mix and developments in demand, such as the uncertainty in the proliferation of electric transportation, forecasting load is becoming ever more difficult for grid planners. In this light, implementation of DR becomes even more attractive in allowing the DSO more flexibility to react to future changes in the demand and supply landscape.

The ADDRESS project – an EU funded project in the area of developing active distribution energy networks – published a report in 2013 which estimates the potential DSO investment cost savings through implementation of wide spread DR schemes [25]. In studying two separate distribution networks in Germany and Spain, they estimate long-term investment cost savings of up to 2.5% and 2.6% respectively, with most of the savings in Germany coming from reduced transformer investment.

In a comprehensive study of the UK distribution network in 2012, Redpoint Energy in [26] found network investment savings from DR of up to 7% in 2020, rising to 14% in 2030 with the implementation of both ToU and CPP tariffs. In a report on future transmission and distribution infrastructure required in the UK network, Imperial College London and Element Energy in [27] found £1.7bn in distribution reinforcement cost savings by 2030 from implementing DR. In a 2010 study, Imperial College London and the Energy Networks Strategy Group in [28] find that up to £10bn in net benefits to 2030 from wide-spread household DR schemes could be realised by the UK distribution network, assuming high levels of EV and controlled heating penetration. Looking more broadly at smart infrastructure in general, in another study of the UK distribution grid, Ernst & Young in [29] suggest that savings from investing in smart vs conventional investment upgrades will save as much as £19bn for the whole distribution network between 2012-2050. Even in a low decarbonisation and electrification scenario, they still expect the savings to be £10bn. They also find a limited downside risk of between £0.2-1bn of investing in smart technology now (report dated 2012) vs waiting until 2023.

Bouorakima et al. in [30] studied the investment economics of DR for a distribution network substation in France with two 36 MW transformers, where there was an option to add a third. Although they were not able to publish financial results due to confidentiality, they were able to show that investment could have been postponed by one year if 6 MW of flexibility was available, and only increments of on average 400 kW extra would provide an extra year of deferral. While 6 MW sounds like a great deal of required flexibility, this only represents 8% of the total max capacity spread across the two 36 MW transformers. For the transmission grid, the European Electricity Grid Initiative (EEGI) produced a study in 2013 which suggests a 10% reduction in investment cost between 2020-2030 could be achieved with smart grid implementation [31]. This would represent a saving of around €7-10bn, set against a required investment in smart grid innovation of only €1bn.

For these savings to be realised however, DSOs may need to play an active role in catalysing some of the developments in the DR and flexibility industry. EvolvDSO – an EU funded project aiming to develop tools to help DSOs cope with DRES integration - believe DSOs need to evolve from a passive to a fully active distribution management system and work closely with regulators, TSOs and new market entrants to ensure a smooth, timely and effective introduction of a flexibility market [32].

DSOs will also need to update their grid investment planning models to incorporate these new uncertainties and opportunities. According to Bernards et al. in [33], a 2015 paper, there are no substantially proven, sophisticated network planning tools as of yet that integrate advanced smart grid solutions or smart market strategies into the optimisation. From our research, this still remains the case – although many new planning models have been suggested (see [34–37]), none appear to have been sufficiently and robustly tested, nor uniformly accepted by DSOs. The exception to this is the 'Transform Model' which has been adopted across the UK and in part in New Zealand [38]. However, the smart grid/low carbon scenario ranges used in this model and their inputs do seem limited in their scope.

Unfortunately for DSOs, due to the significant future uncertainties, there will be increased risk involved in how they plan their grid investments going forward. What will be important is to follow a strategy that allows them sufficient flexibility to deal with this future uncertainty but also ensure they are not too late with relatively small investments in technologies like DR, that could provide much larger savings in the longer term.

In their assessment, Bernards et al. [33] stress that not only should future planning include both classical and smart grid solutions, but the optimisation should also consider the huge number of extra parties involved when assessing the smart grid solutions. This is the major difference between classic and smart grid scenarios – in the past DSOs only need consider the expected growth in demand of their users, now they must consider all manner of developments on both the supply and demand side, and how they should place themselves in the smart grid market to benefit most out of the future developments.

In a 2016 report for the National Infrastructure Commission in the UK, University of Cambridge and Imperial College London researchers suggest future DSO infrastructure planning should be treated as an investment portfolio – employing various asset classes with differing performance characteristics in terms of cost, energy capability and flexibility [39]. Such a portfolio would contain a mix of both flexible assets to manage the uncertainty period and long-term strategic commitments that could be deployed once uncertainty has been resolved.

Despite the challenges in updating network planning models, it seems likely from the above evidence that DR and smart grid infrastructure do provide DSOs with the potential for investment cost savings and the ability to better cope with the uncertain demand and supply landscape of the future. More detail on DR itself and the evidence on its impact on peak shaving will now be discussed in the following sections.

3.2 Demand Response: An Overview

The definitions of DR vary between sources, however the U.S. Department of Energy in [40] neatly defines it as:

> *"Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized."*

The first part of this definition refers to changing electric usage in response to a change in prices. An example would be reducing the temperature, and therefore consumption, of an electric heater in response to an increase in electricity prices at a certain time of day. This action can simultaneously reduce the need for production and/or grid capacity, whilst rewarding the end consumer with an electricity cost saving (if we assume this consumption will be shifted to another part of the day when prices are lower). This action could either be taken manually by the end consumer or automatically controlled by a device that has received a signal to do so, e.g. a smart meter.

The second part of the definition refers to incentive payments and is important as although it is likely that end consumers will expect some compensation in exchange for their demand flexibility, the demand shift itself may not be solely in response to a change in prices. In some cases, the demand will be shifted for other reasons, such as to reduce load at critical peak periods when "system reliability is jeopardized", i.e. the basis of our project. Indeed, end consumer prices could be set higher during critical peak periods in order to encourage lower consumption, but it is not a pre-requisite for the DR. In our pilot study to be discussed in more detail in chapter 5, the participants have been offered a reduced tariff for all electricity consumption, i.e. not time-specific, and their electrical load will be automatically controlled and reduced during periods of peak load in the AEN network.

Whichever definition is chosen, previous literature makes it clear that DR is focused on changing end consumer demand, or electrical load, during certain time periods, in response to a signal of information. To have a clearer picture of which electrical loads can be shifted, when and by how much, various authors have attempted to define loads into different sub-categories. This is also useful for grouping various different DR appliances into groups when modelling how they would be controlled.

The definitions of these load categories have evolved through various literature written around the optimisation of a collection of DR appliances, see [41–46], and we believe the most useful is by Ottesen and Tomasgard in [47]. In this paper, Ottesen and Tomasgard develop a decision model for scheduling load for future time periods in a Norwegian university building. Their definition of loads in Table 3-1 are therefore used in order to clearly define the constraints of each DR appliance in their optimisation model.

Load Category	Load Sub-Category	Description	Example Appliance
Shiftable load	**Shiftable profile load**	Load can be moved but the profile remains the same	Washing machine
	Shiftable volume load	Total volume of load must be met over a time period, but profile can change within limits	Boiler/Heating
Curtailable load	**Reducible load**	Load can be reduced without switching off	Dimming lights
	Disconnectable load	Appliance is either on or off	Industrial processes

Table 3-1: Load categories as defined by Ottesen and Tomasgard in [47].

As each DR appliance will have a different use pattern and load profile, it is important to group each appliance so that the controlling architecture (e.g. signal receiving smart gateway) knows how to manage the appliance. For example, the consumer will always require that a television set is available to turn on and off at any time, however for a heater it does not necessarily matter when it is turned on and off, as long as the end consumer maintains a certain level of comfort – say within a pre-defined set of temperatures.

As in [47] and many other studies of DR, due to the complexity of controlling many devices at different time periods, it is implied that the DR appliances will need to be automatically controlled by some form of smart infrastructure. The alternative to this would be a human present at all relevant times, manually managing the load of each appliance. Although this could be arduous for a large university building such as in [47] or even a household with several appliances, manual activation is an option for a smaller set of appliances. Especially when one considers the human intervention requirement of certain appliances, such as having the clothes ready to be washed to use your washing machine or having the electric vehicle home and plugged in for it to be charged or discharged. Indeed, this is where much of the past DR research has focused. However, many of these studies, which typically looked at exposing end consumers to varying prices and expected a manual response, often reported 'response fatigue' in participants where the user tires of continuously checking prices, resulting in decreased involvement or a switch to non-dynamic pricing schemes [48,49]. Although some papers report more longevity for manual response to price changes [50], there is significant evidence that automated DR improves the response levels [51], sometimes by up to 200% compared with manual DR [52–54].

Whether the load change is manually or automatically induced, it is generally accepted that the end consumer should be rewarded for providing this flexibility in consumption. This is due to the current status quo of the end consumer being able to use any device in their building, at full power, at any time of day. If asked to change their habits, and potentially not consume when they would like to, they naturally would expect to be rewarded – financially or otherwise – for this change in behaviour.

One interesting study, however, puts a question mark as to whether end consumers should be rewarded for their flexibility. Gamma et al. [55] at St. Gallen University consider the reverse scenario in which not participating in a DR program would deliver the end consumer a punishment in the form of an extra service fee. In a small study of 151 participants they found more people were likely to participate in DR programs if they were subject to punishment, than if they were subject to reward. According to Gamma et al. [55], these findings are consistent with the general psychological principles of prospect theory and loss aversion, as defined in [56]. This approach of punishment is not too dissimilar to peak pricing tariffs discussed in section 2.6.2 of this thesis, where the 'punishment' is a higher price of electricity to the end consumer if used at certain critical peak periods. Nonetheless, although punishment may in general cause more behavioural change than reward, there is little other academic support for this approach of the consumer effectively always paying for free use of their appliances.

However, this research still provides an interesting perspective on an alternative method in delivering flexibility to a future electrical grid.

Accepting the current status quo of offering reward for flexibility, whether this reward should be directly linked with prices is another question. Following on from the definition of DR provided by the U.S. Department of Energy in [40], this report also identifies two types of DR programs: 'price based schemes' and 'incentive based schemes'. Price based schemes include the typical tariff structures discussed in section 2.6.2 and in much of the literature such as ToU, CPP and Real Time Pricing (RTP) or Dynamic Pricing. All of these schemes expose the end consumer to different electricity prices throughout the day, in order to induce a change in demand. In incentive based schemes, consumers are given load changing incentives that are separate from their normal electricity rate. This could be in the form of a payment or in theory any other non-financial reward such as a guarantee of carbon emission reductions. Non-financial rewards are mentioned as there is numerous evidence that consumer motivations for participating in certain schemes can be purely environmental or perhaps even just an interest in new technology. Consider, for example, the huge increase in green marketing on all kinds of products and more specifically, the introduction of green electricity tariffs around the world [57] – which often offer nothing more than to source part of the end consumer's electricity from renewable sources. Interestingly, however, some research on green electricity tariffs has found a gap between implied demand for these tariffs from environmental willingness to pay surveys and actual adoption of the green tariffs [58–61]. General consumer acceptance to DR programs will be discussed in section 3.5, but this provides one insight into perhaps why most literature on DR to date has focused on financial incentives to end consumers.

3.3 Review of Previous Academic Literature

3.3.1 United States

The U.S., particularly California, were quite early in testing various DR schemes trying to induce peak demand reduction. This was in response to the infamous blackouts during the California electricity crisis of 2000-01 [62]. In 2010, Faruqui and Sergici in [63] presented a review of 15 price based DR studies looking at peak demand reduction in households. Figure 3-2 shows a summary of the peak load shifts achieved by the various studies across the U.S. ToU, CPP and RTP pricing types have already been defined. With Peak Time Rebate (PTR) the end consumer is offered a rebate for each kWh of reduction during critical hours. 'ToU w/Tech', 'CPP w/Tech' and 'RTP w/Tech' refers to programs that involved 'enabling technologies', i.e. some form of automated control of the DR. All other results in Figure 3-2 were from DR programs that required manual intervention from the end consumer. The studies range from 1996-2007, twelve in the U.S., one in Canada and one in Australia. The fifteenth study is from France and is not included in Figure 3-2.

At first glance, the achieved shifts in peak load seem very high – above 50% in some cases. However, many of these studies are conducted during summer months in very warm parts of the U.S. where high load air conditioning units are used. Shifting this load by, for example, 'pre-cooling' the household before the critical peak period can dramatically reduce demand. Also, some studies report the reduction of a specific peak period and some report the average reduction peak across a whole day. Nonetheless, this summary of results shows two key findings: 1) CPP schemes induce more peak reduction than ToU or RTP schemes and 2) automated DR schemes generate more demand reduction than manual schemes. These two results are consistent with both ideas presented in the previous section: 'punishment' in CPP pricing producing more response than reward and 'response fatigue' leads to lower response in manual DR schemes.

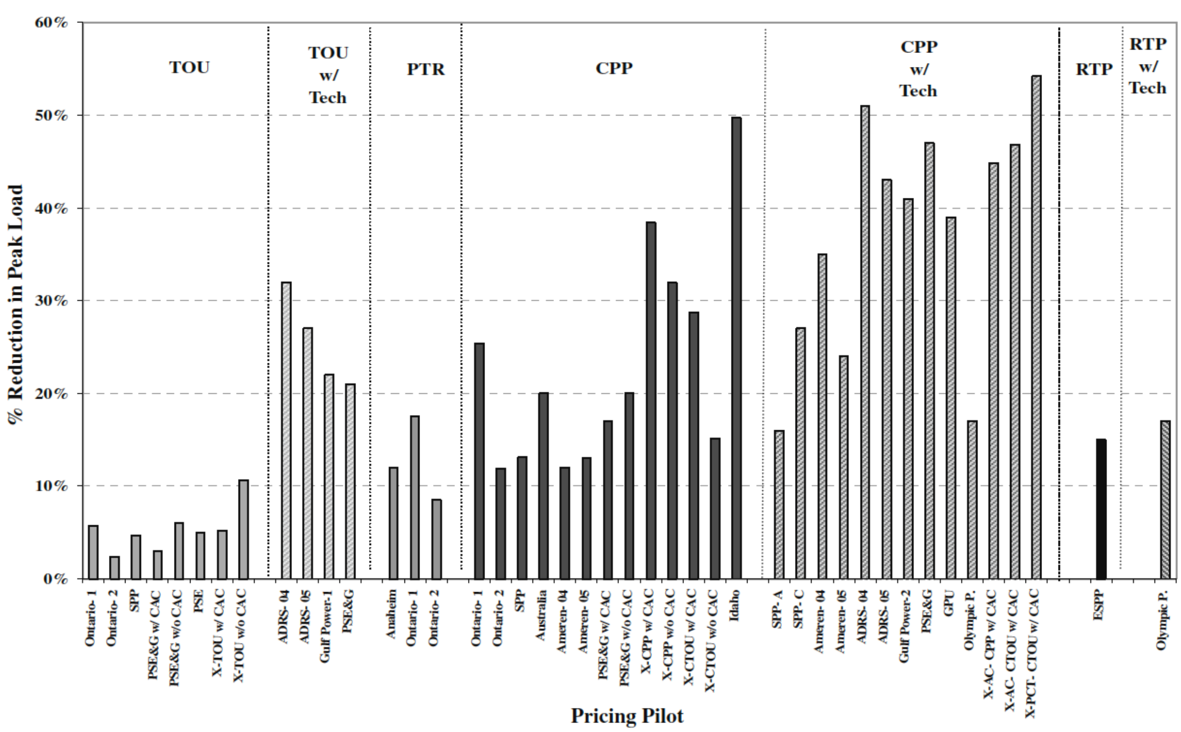

Figure 3-2: Summary of DR studies from Faruqui and Sergici in [63].

3.3.2 Europe

In Europe, literature delivering quantifiable levels of peak demand reduction are less extensive. The California electricity crisis helped the U.S. focus its attention on peak demand reduction and delivering wide-spread smart metering in households. Europe has seen less practical research in this field, due to different focus points in each country. Indeed, DR has become more of a focal point following the large-scale introduction of intermittent RES, often introduced at a distribution level, requiring a more flexible electricity network. European research has therefore tended to be more theoretical and estimatory in nature.

Nonetheless, there is some literature and what most European papers do consider are setups where the DR is activated automatically by smart infrastructure. Automated DR has consistently shown better results and is the method used in our SEMIAH pilot discussed in chapter 5, and is assumed in our simulation of a flexibility market in chapter 6. Stamminger and Anstett in [64] studied 67 households in Germany, all with smart meters so that consumption could be monitored and 41 with smart appliances – washing machines and/or tumble dryers. The consumers were exposed to hourly price changes during a test period of two years and were able to either manually adjust the operation of the appliances or program them to start at times of low prices. The results show the end consumer could save 28% on the electricity cost of using these appliances and estimate a 10% reduction in total demand in the house is possible, from just these appliances. They make no estimates of particular peak reductions however, as the focus of the study was more on balancing the production from wind and solar.

In the Netherlands, Kobus et al. in [65] tested 77 households and found that automatically programmed smart washing machines could reduce evening peak consumption of the washing machine by an average of 48% versus the control group with non-smart appliances.

In Belgium, D'hulst et al. in [66] studied a total of 418 programmable appliances across 186 households as part of the LINEAR pilot project[12]. Some smart boilers (15 deployed) and electric vehicles (7 deployed) were used as 'buffers', i.e. storage or off-loading devices. Each boiler contained 200 litres of water and had nominal power of 2.4 kW. The participants received an incentive payment of EUR 1 for every 40 hours of flexibility they offered. They found that each household could achieve an average maximal decrease of 65W for a 15-minute evening peak period by controlling the smart

[12] http://www.linear-smartgrid.be/

appliances. For the boilers, an average maximal power decrease of 300W or 12.5% of the boiler load can be achieved, this time over a sustained 10-hour period.

Using the same LINEAR pilot project in Belgium, Vanthournot et al. in [67] control the same set of appliances with the objective of minimising end consumer electricity costs based on day-ahead ToU pricing. Vanthournot et al. find that although some small cost savings on each appliance are possible – around 10% on the 'wet' appliances and around 5% on the boiler – the total cost saving for the household and the total available flexibility is not significant. The paper recommends aggregation on national levels for effective results.

3.3.3 Norway and Sweden

In the northern Nordic countries of Norway and Sweden, due to very low winter temperatures and high penetration of inefficient electric panel heaters, DR research has focused on space and water heating. In Sweden, space heating represents around 50% of total residential power demand [68]. In Norway, space heating represents around 64% of total electricity consumption and water heating (boilers) 15%, see Figure 3-3. This means that the average Norwegian household uses around 80% of its electricity on heating alone.

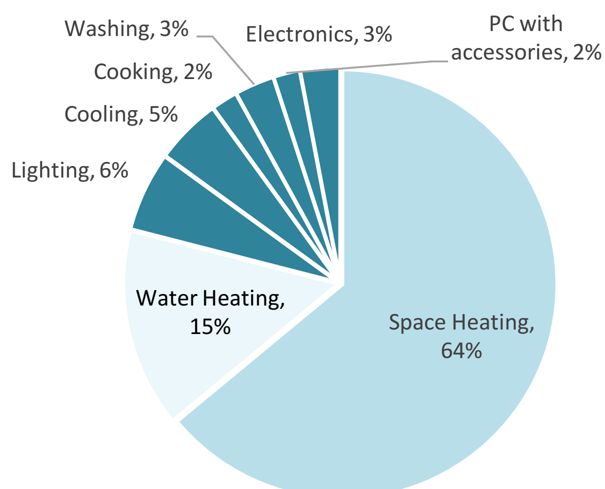

Figure 3-3: Average Norwegian household electricity consumption by appliance, from [69].

Svalstedt and Lof in [70] studied 214 Swedish households with programmable space and water heating systems, as part of the Smart Grid Gotland pilot project[13]. Each household was exposed to a 'smart customer price' which included an RTP element linked to the NordPool spot exchange, a ToU element for the peak period of 6am to 10pm between November and March, and a wind component linked to the wind turbine generation on Gotland (an island in Sweden). Svalstedt and Lof found total demand reductions of 16% across the five most price expensive hours of the day.

Bartusch and Alvehag in [50], working in co-operation with a Swedish DSO, exposed 97 households to a ToU tariff which was dependent on the average of the five highest hourly meter readings during their peak period of 7am-7pm. Appliances had to be manually adjusted by participants and space and water heaters were considered to have the most significant DR potential. Over the six-year study period, each year Bartusch and Alvehag found mean reductions in peak demand levels in winter months of between 8% and 22% in houses and between 1.2% and 10% in apartments. The lower reduction in apartments is likely due to their use of district heating (i.e. centralised), as opposed to higher load, less efficient panel heater in the houses.

Sæle and Grande in [71], studied a pilot of 40 households in central Norway: 10 percent of which had 12-15 kW electrical boilers for hot water and space heating and the remaining 90 percent had standard 2 kW boilers for hot water only. Both were automatically controlled by signal receiving smart meters. For one year, the participants were exposed to a ToU tariff based on historic day-ahead price peaks in the central Norway area (NO5) – between 8am-10am and 5pm-7pm. In addition, a sticker was placed on other appliances, such as washing machines, to remind the participants of the peak hours to also induce some manual DR. The reduction during the morning peak for households with standard boilers was approximately 1 kWh/h and for space heating boilers was approximately 2.5 kWh/h. The kWh/h unit refers to a total of 1 kWh of energy saved per hour. In other words, instead of an instantaneous peak of power in kW, imagine a continuous peak over a one-hour period, where the total energy used is in kWh. This is the same as the peak you would see if you were to look at hourly consumption or hourly spot volumes. Although not exactly the same as an instantaneous peak, it still provides a very relevant picture of peak reduction.

[13] http://www.smartgridgotland.se/

Sæle et al. in [23] studied 48 households equally split between the Demo Steinkjer[14] site in northern Norway and the Smart Energi Hvaler[15] site in southern Norway. Each household was exposed to a new kind of network tariff designed by Sæle et al. which charged consumers an extra fee per unit of energy which went above a pre-defined maximum peak hourly energy consumption, or as they called it “subscribed power” (as referenced already in section 2.6.4). The participants pay a fixed charge per kW of power up to this subscribed power peak, set at 70% of the maximum peak hourly consumption for the previous year, and then pay an extra variable charge for all hours where total kWh consumption exceeds this peak. Participants were given technology enabling them to visually monitor their consumption in kWh, kWh/h and cost. During a 2014 winter period of January 15 to April 1, Sæle et al. recorded a reduction in total consumption of 5.3% in the northern pilot and 16.3% in the southern pilot, as compared with the same period in 2013. They also saw far less peaks above the subscribed power level in the total 6-month study period as compared with 2013.

Using the same Smart Energi Hvaler pilot in southern Norway, Bremdal et al. in [72] used smart energy management systems to control heating and boilers of 30 participating holiday cottages. Tests were run for consumption when residents were either present or away from the home, still requiring some energy to avoid freezing of equipment and pipes, e.g. a recommended house temperature of no less than 4°C. Bremdal et al. were able to achieve an average peak power reduction of 2.3 kW and an average hourly reduction of 480 Wh/h per household. Bremdal et al. also extrapolate this for the whole Hvaler area and estimate an average reduction of 2.2 MWh/h could be achieved if 10% of the 4,600 cottages were involved in using their automated energy management system. Whether this reduction would be able to coincide with a relevant critical peak period for the local grid was not discussed.

An earlier study in 2009 by Ericson in [73], specifically analyses potential peak demand shifting of 2 kW boilers used for hot water in 475 Norwegian households. Using six months of historic data collected from the households (such as hourly consumption), Ericson simulates the potential peak shifting that could have occurred during the period, without significant impacts to the user’s comfort. Ericson expects reductions of 0.35 to 0.58 kWh/h (18-29%) in the morning hours and 0.18 to 0.59 kWh/h (9-30%) in the evening hours are achievable.

[14] https://www.demosteinkjer.no/

[15] http://www.smartenergihvaler.no/

3.4 Review of Previous Pilot Projects

In addition to the various academic literature discussed above, we would like to highlight some industry smart grid pilot projects that have provided some interesting results in the field of DR and peak shaving. These results differ slightly from above as they have not been published in peer-reviewed academic journals. However they do still provide valuable results within this field and often the same researchers that have contributed to the above discussed literature work alongside these pilot project, e.g. Sæle et al. in [23] working with the Demo Steinkjer and Smart Energi Hvaler sites in Norway. We examine only pilot projects that have not already been discussed in the previous section.

EcoGrid EU, Denmark

Located on the Danish island of Bornholm, EcoGrid EU[16] was one of the first large-scale smart grid test sites in Europe. Funded by the EU and Energinet.dk (the Danish TSO), and involving many other international partners, the project comprised of around 28,000 households (55 MW peak load) with local generation capacity of around 40% renewables (35 MW wind power) [74]. The DR test was a real time pricing (RTP) experiment with automatic control of either heat pumps only, direct electric heating only, direct heating and water heaters together or a combination of the above. The results for direct electric heating only were an average of 1.9% peak load reduction. All other combinations of devices were around 0.7%. Although 1.9% does not sound vast, this represents a decrease of 1 MW across the whole 55 MW system [75].

GRID4EU, France

In a consortium of 6 DSOs from separate countries, along with 21 other organisations from 15 different countries, and with a budget of €54 million, GRID4EU[17] was one of the largest and most international smart grid projects in Europe. Completed in January 2016, the project contained a residential peak shaving experiment with customers of the French participating DSO. During the winters of 2014 and 2015, 217 participating households were offered gift-vouchers in reward for significantly reducing electricity consumption between 6pm and 8pm on 20 selected peak demand days. 40 of these households also has their electric heaters controlled by a smart meter. On these peak

[16] http://www.eu-ecogrid.net/

[17] http://www.grid4eu.eu/

demand days, customers reduced their power consumption by 21% on average, between 6pm and 8pm [76].

Customer-Led Network Revolution, UK

As part of one of the largest smart grid projects ever conducted in the UK, the Customer-Led Network Revolution[18] project conducted by Northern Powergrid, a DSO in northern England, contained three DR studies carried over one year between 2012 and 2013. 628 consumers were exposed to ToU tariffs and required manual consumption changes; 8 consumer's heat pumps were automatically controlled; and 96 consumer's smart washing machines were controlled. The ToU trial resulted in an average of 8% peak demand reduction, calculated comparing the year-on-year difference between the average of the highest half-hour peaks for each day. The other two tests did not provide any meaningful results, in part due to communication errors between the smart devices [77].

3.5 Consumer Acceptance and Privacy

The above studies and pilots show a varying degree of success in moving demand and reducing peak consumption. There are many different reasons for the variation in results – such as total controllable power, flexibility of appliances, predictability of load – but one element that is consistently considered is the views of the end consumer and how this impacts the outcome. How willing, and to what extent, the end consumer participates in a DR scheme, to give automatic control of certain appliances to a third party, or to provide access to their private data. All of these unknowns are of significant importance in predicting the success of large-scale DR in the future. Almost all pilot studies in DR require participants to sign up voluntarily. This means that virtually all results in previous studies are delivered by end consumers that already have an interest in participating in DR, for various reasons. If DR is to be applied in a much larger scale, many of the end consumers may be less willing to accept certain conditions of a DR system.

We touched on one aspect of this broad topic in section 3.2 when discussing the 'response fatigue' effect when end consumers are expected to always manually adjust appliances during peak periods, see [48,49]. Although this is a significant factor, the largest household loads, particularly in countries like Norway, tend to come from

[18] http://www.networkrevolution.co.uk/

boilers and space heating or cooling system which can relatively easy be automatically controlled. Appliances requiring some manual intervention, such as washing machines, typically form quite a small part of total demand and are therefore less significant to the future potential of DR. Electric vehicles and other high load devices of the future may, however, fall into this manual category. We will discuss these future technological developments and how this may impact the potential of DR in chapter 4.

Once solving the problem of response fatigue with automation, the potential for DR will still be dependent on the willingness of participation from the end consumer – when they will allow automatic control of devices, if at all, and what flexibility of comfort settings they will allow. For example, a desired indoor temperature range of 18°C to 24 °C provides more flexibility than a range of 20°C to 22°C.

In terms of consumer acceptance, many authors believe segmentation of consumers into different target groups is key to improving the take up DR programs or smart grid technology in general, see [78,79]. He et al. in [79] define five different DR contract types which should be able to match with each consumer's load mix and general preferences. He et al. also describe two example consumers: 1) a well-educated consumer who is risk seeking in order to maximise financial compensation but is also concerned about privacy. A dynamic pricing or RTP contract may suit this consumer, giving them their desired freedom of consumption, with maximum possible financial gain, limited release of private data for control and the complexity of the program is not a problem due to good education. 2) A less-educated consumer, more willing to outsource the handling of complex technology, perhaps at a small cost. An automated load control contract, based on ToU pricing may suit this consumer.

Even with this choice of consumer focused contract types, He et al. [79] accept that there are still significant barriers to explaining which contract would be best for the customer and convincing them of the value of the DR program. In addition, He et al. discuss who might be the actual intermediary involved in providing this DR service – whether it be an energy supplier or DSO, a third-party such as an aggregator, or even a non-profit consumer cooperative – and how consumers' perceptions of this intermediary and its goals may affect DR participation. Each of these potential intermediaries has a pre-existing consumer reputation, which can vary from country to country. Furthermore, in countries with a highly concentrated energy supplier market and monopolised DSOs, i.e. Norway and most of Europe, if these organisations were to be the intermediaries of DR programs, there is also strong potential for an abuse of market power, leading to further consumer discontent.

In a review of the findings of an international project on DR customer interaction, as part of the International Energy Agency Demand Side Management Implementation Agreement, Hull et al. in [80] also highlight the need for consumer choice, with an emphasis on not providing too many choices that may confuse or stress the consumer. Also discussed is the importance of providing an easily understandable and tangible benefit to the consumer, and the importance of the way the DR program is marketed. Similar to the previous ideas of punishment providing better results than reward, Hull et al. site a well-established theory on how to frame a concept, from Tversky and Kahneman in [81]. Hull et al. suggest that up take of DR programs may be higher if consumers are explained what they would be losing if they were not to join, such as worse environmental quality from higher carbon emissions, than explaining them the benefits from joining.

One other key aspect of consumer acceptance, particularly when dealing with automated systems, and touched on in He et al.'s [79] DR contract definitions, is that of privacy. For DR programs to be effective, the intermediary controlling your household devices or providing smart metering information will need access to more private information about your household than in previous scenarios. For example, regular monitoring of total electricity consumption, monitoring consumption on each appliance or monitoring and controlling the indoor temperature of your household. Although seemingly innocent pieces of information, one could easily imagine how knowing whether certain appliances are on or off could be considered an invasion on one's privacy. Not least, as a simple example, because minute-by-minute household consumption data could be valuable information if somebody wanted to plan a burglary. Households additionally may just be uncomfortable with the idea of a third-party having full control of their heating system.

In a review of cyber security threats for smart grids, Line et al. in [82] identify three major concerns for consumer privacy, particularly when considering monitoring the use of individual appliances. First is the burglary example mentioned above, second is marketers using the data for targeted advertising and third for law enforcement monitoring home activities to detect criminal activity, e.g. illegal drug production.

Line et al. [82] also outlines a number of other challenges to smart grid implementation, including an increased threat of cyber attack, again adding to consumer data privacy fears. These concerns are echoed in a report on smart grid risk from the Norwegian research institute SINTEF [19] for The Norwegian Water Resources and Energy

[19] http://www.sintef.no/

Directorate (NVE), where vulnerability of unsecure software in particular is highlighted as one of the main threats to smart grid data security ([83], cited in [84]).

Nonetheless, some recent surveys of Norwegian electricity customers have shown quite high support for the introduction of new technology. Livgard in [85], from surveys of more than 8,000 energy customers collected between 2006 and 2014, show that positive support for smart metering increased during that period to a high of 66% for users currently without a smart meter. Interestingly, positive support from customers already with a smart meter is much higher at 85%, affirming happiness with the product. Additionally, 70% reported they do not have any security fears regarding the implementation of smart meters. However, 26% reported they were uncertain how secure the new technology is. Even though the respondents may accept the technology, only 23% expect that hourly meter readings will make them change their consumption patterns, and 46% consider it unlikely they would move their consumption to periods when prices are lower. The study did not however provide consumer likelihood of allowing automatic control of consumption or likelihood of reducing consumption in higher price periods. A 2015 study of UK electricity customers by Fell et al. in [86] reports strong acceptance for automated 'direct load control' of heating devices in combination with a ToU tariff providing cost savings. This was despite the expectation of unpopularity due to loss of control, as suggested by evidence referenced in their literature review.

4. Tomorrow's Power System

The shift away from fossil fuels and the continuous progress in technologies lead to new requirements for power markets. More renewables and decentralised electricity generation require a more flexible energy system. Beside technology, new roles and responsibilities must be created and assigned. Market frameworks and policy should be designed to be as neutral and open as possible to encourage new ideas.

As of now, most countries still have market frameworks in place that are based on centralised generation and usually do not make it easy for wide-scale DR solutions to be implemented. This chapter will discuss future market frameworks where flexibility and DR may take over a fundamental role and gives an overview about the most relevant developments on the demand side.

4.1 Future Developments & Trends on the Demand Side

Even though residential electricity demand in Norway and all over Europe has been relatively constant over the last 10 years, the number of electric devices in our daily lives has steadily increased. That the total consumption is still stable is partly due to increases in energy efficiency [87–89]. In the long-term however, electricity consumption is likely to increase again due to the electrification of transportation and other devices. Electrification could drive consumption absolute and per capita. An example is the increasing share of electric vehicles (EVs) in Norway.

As a result of Norway's EV policy, market shares of new cars sold climbed to 29% in 2016 – 15.5% purely battery driven EVs and 13.8% plug-in hybrids [90]. EVs now contribute 2.6% to the total Norwegian car fleet [91]. Charging a 70 kWh battery of a Tesla Model S with 11 kW takes approximately 8.5 hours [92]. This has two dramatic effects on the power consumption of a household. Capacity and total electricity consumed would increase abruptly. The median peak consumption of the households in our pilot study, discussed in the next chapter, is 5 kW. Consequently, the peak consumption of a typical household can more than triple. Also, the total consumption could hugely increase, depending on the actual usage of the Tesla.

As seen in section 2.6, the important driver for grid costs and investments is grid capacity, which could drastically increase if many households buy EVs. EVs are not the only device that can lead to significant jumps in the required grid capacity however. Other devices with a high nominal power such as induction stoves and tankless water heaters become a real challenge for grid companies. Induction stoves can reach between 4 and 7.5 kW maximal nominal power [93] and tankless electric water heaters above 10 kW.[20] The advantage of those devices is higher efficiency than normal electric stoves and traditional hot water boilers. Total energy usage will be lower, while the maximum power increases significantly.

This shows the importance of an appropriate pricing of capacity. If a consumer pays the same grid tariff installing a tankless electric water heater as a traditional hot water boiler, he will go for the first one. The consumer saves energy and therefore money. If the pricing of capacity is sufficient, the first option is less certain since the consumer is charged their fair share of the grid costs.

Tankless electric water heaters are not only difficult for DSOs, they also replace one of the simplest storage possibilities for electricity, boilers. This has negative consequences for the success of DR. It therefore might make sense from a DSO and regulator point of view to curb the spreading of those high-power devices if there is not a clear benefit for society.

4.2 New Market Frameworks

Developed electricity markets no longer follow a classic downstream model based on centralised generation. Decentralised production and DR have already found its way into the markets and will strongly continue to do so, even though so far mainly on the medium to large consumer level. While it is relatively easy to exploit the flexibility of medium and large consumers, it is more difficult to do the same with small consumers and households. The gained flexibility per unit of investments is much lower. Hence, the energy sector is lacking lucrative business models that effectively exploit small flexible units and consumers [94].

However, the fact that the industry faces many difficulties to make DR profitable on a small scale is not the only issue. Market frameworks in many countries are a real burden to implementing new business models. The minimum requirements for ancillary

[20] The Bosch Tronic 6000 C has a nominal power of 17.3 kW in the less powerful version [116].

service markets are too strict for demand side units. The same is true for DSO regulations. While DSOs could play an important role for the development of flexibility markets and DR, their regulations obliged by the government are often outdated and do not provide incentives for innovative approaches [94,95].

The implementation of new market frameworks could clear the way for DR. Many governments have identified the need for change and originated task forces and research projects such as in Norway [94]. One of the front runners is clearly Denmark, who want to implement flexibility solutions within the next ten years to provide stability to its wind powered system [96,97].

Flexibility in this context means the capability of shifting consumption or production of electricity to another point in time. Hence, flexibility can have many forms and is not limited to the demand side. The difficulty lies in unlocking demand units, since supply side units can often be controlled more easily. Even wind and solar can be disconnected if necessary. It is important to note that through flexibility the total amount of electricity generated or used does not change. Using advanced technology and new data insights, flexibility exploitation could lead to efficiency gains but this is not a prerequisite.

Flexibility can be used for many different purposes. The Danish Energy Association and Enrginet.dk see the most potential for TSOs to keep the power system in balance and for DSOs to reduce grid investments [96]. Those two business cases are not the only ones. The Smart Energy Demand Coalition (SEDC) [95] defines three basic models on how flexibility can be exploited: implicit demand side flexibility, explicit demand side flexibility and local optimisation.

Implicit demand side flexibility is an optimisation of consumption against the market price. As a result, the electricity bill will be smaller. The steering of consumption would mostly work through automatically controlled DR. Several providers all over Europe already offer such a service today. This model brings the service provider further insights into consumer behaviour, which could have positive effects on efficiency.

Explicit demand side flexibility is when consumers sell their potential of shiftable load via an aggregator. The aggregator can sell the accumulated flexibility to TSOs, DSOs and all other market players that need balancing or system support services. One of the challenges is to provide consumers enough incentives to participate in such programs. Based on today's pilot projects, the main rewards for households are free information about their efficiency, better control of some devices and some financial benefits.

Local optimisation concerns prosumers who are consuming and producing electricity, e.g. with rooftop solar. By coordinating demand and supply, the household electricity usage can be optimised and the grid is supported. In other words, the self-sufficiency factor of a house is increased.

The explicit demand side flexibility model, which is analysed partly in this work, is the most complex but also holds the biggest potential. Today, a flexibility market for DSOs does not exist and is a simple theoretical construct. Demand side flexibility sold to TSOs and power exchanges is already a reality but only on a small scale. Since DSOs are part of a highly regulated sector, incentives to initiate dramatic changes in the system are rather low. Thus, the regulator and TSO are asked to drive the innovation in a new market design in close cooperation with the DSOs.

One of the biggest barriers for DR is therefore current regulations and the speed of their adjustments. Another crucial factor that will determine the success of DR is the relation between the value of flexibility and DR technology cost. Margins are relatively low and aggregation of enough households is still challenging. Both factors, the flexibility value and the price for DR per unit, are still difficult to quantify, although the cost estimation is easier [94].

The value of flexibility is driven by its demand. Thema [94] identified potential positive and negative drivers of demand for flexibility and their effect on the value. While it is clear how each driver would influence the market, the development of the drivers themselves is unclear. Thema identified the most significant uncertainties for the future development of demand for flexibility as price volatility, ancillary service market participants and distribution grid capacity.

A relatively new technology that found significance in 2016 was 'blockchain'. The main function of blockchain is the storage and encryption of transaction data in a long chain of data blocks. This allows decentralised matching of demand and supply and makes classic financial and settlement intermediaries redundant. The technology is said to have an enormous potential and to heavily push forward decentralised transaction and business models. In energy markets, blockchain could enable private prosumers to trade flexibility or power between each other and thus make energy suppliers, at least partly, redundant. A pilot project that has received much attention is Brooklyn Microgrid[21].

[21] http://brooklynmicrogrid.com/

The houses in the project can sell their surplus roof-top solar production to neighbouring houses. Transactions are steered centrally by blockchain technology [98].

However, the blockchain technology is still in its infancy and is not ready to be implemented on a large scale yet. When this changes, new business models become possible and market frameworks in the electricity sector could change dramatically.

4.3 New Roles and Responsibilities

Flexibility and DR markets create new roles and responsibilities in the power markets. The new roles of the Aggregator and Energy Service Company (ESCo) are referenced most frequently. DSOs are likely to be assigned additional responsibilities and tasks in the long run. There is also a high chance that energy suppliers will see their business models and service offerings changing [94–96,99,100].

The key to the utilisation of residential flexibility lies in the role of the aggregator. They will accumulate flexibility of individual households and exploit this on the market. Thus, the aggregator is a technology provider and contractual partner to the private households. The aggregator will need to convince enough participants to join their network by providing financial incentives or other benefits that will allow him to participate in all the relevant markets. To be able to trade power, the aggregator needs to be registered as a BRP.

It is of great importance that the aggregator possesses a highly standardised technology so he can keep installation and operational costs low in each household and connect to the different systems needed. Another important factor for the aggregator's success is the automatisation of DR so that customers are not bothered by the processes going on in the background. Comfort settings will guarantee the consumers that they can continue to use their devices as they want to. For instance, the consumer should be able to set temperature limits in his house that are guaranteed, even if the heating system is used for DR. If the consumer wants to change the comfort settings he should be able to do so at any given time [95,96,99].

ESCos provide additional services to households or other demand side parties based on smart technology. ESCos do not offer aggregated flexibility to other market players, rather they provide smart services or data insights to their customers. If they commercialise the flexibility of a customer it would be to their own benefit, e.g. increase use of the flexibility of a house to minimise its grid costs rather than to provide ancillary services [99].

The role of an aggregator or an ESCo can either be an additional third party that is newly established or be taken over by a market player such as an energy supplier. Due to the small margins in residential flexibility markets, already established market players are most likely to take over those roles or the roles will be combined into one party. However, it is not impossible that pure aggregators or ESCos will be able to establish themselves in the future power market.

4.4 The Future Role of DSOs

In the past, DSOs have been assigned clear roles and tasks in the power system. Their responsibilities have been the operation, maintenance and development of the distribution grids, as well as data management of losses. Hence, DSOs have had a rather passive role. The new requirements for the power grid and the system as a whole will challenge the traditional role of DSOs. The Council of Energy Regulators [101] has looked at the potential development of the DSO role in the future and have defined different fields which potentially bring new activities for DSOs.

As already discussed in this work, potential new activities for DSOs could be related to RES penetration and flexibility needs. Aggregators will provide DR services that do not have to be offered by the DSOs. Nevertheless, the DSOs would be able to use those services to prevent voltage and capacity constraints and to avoid grid reinforcement if efficient enough. Ancillary services are so far a matter for the TSO. In the future, this could change and DSOs could take over some local dispatching roles, stabilising the grid on a lower level.

DSOs can be involved in the infrastructure of electric and gas vehicles. Even though the operation of fuel stations is a competitive field not normally allowed for regulated monopolistic entities, the DSO is important for the development of recharging points and fuel stations. The building of a fuel station network may require additional grid investments. Furthermore, the DSO should monitor the power usage of those stations for a more efficient management of the grid.

Other activities DSOs may take over are related to the management of meters and data. In Europe, smart meters are largely owned and manged by DSOs. Not all countries follow that approach and some make metering a competitive market. In addition to the technical installation, the management of the data is a potential task for the DSO. When their customers switch energy suppliers, the DSO should ensure the transfer of the data and the connection to the new supplier. Several data handling models are possible.

Although DSOs will not be offering energy efficiency services alongside DR, they may be responsible for establishing appropriate incentives by setting tariffs as described in earlier chapters. The right tariffs could set incentives for customers to increase energy efficiency through manual or automatic DR.

5. The SEMIAH Pilot

5.1 Introducing the Problem: Load in the Distribution Grid of Agder Energi Nett

The SEMIAH project – Scalable Energy Management Infrastructure for Aggregation of Households – is an EU funded European research project with the aim of making technological, scientific and commercial breakthroughs towards implementation of DR in households. The consortium of partners working on the project includes various universities, research institutions, DSOs and software companies from across Europe.[22] The partners that we worked with in this thesis are the DSO for the Sørlandet region of Norway – AEN – and a Swiss software company – Misurio AG.

There are two pilot test sites, one in Norway and one in Switzerland, in which DR is used to shift load for various objectives. In Norway, the pilot test location was chosen by our partner AEN, as one of the main objectives for the Norwegian pilot is for AEN to test whether DR could be a cost-effective tool to reduce load at critical pressure points in their grid. AEN have identified the pressure point as a transformer in the Engene region. This transformer is connected to 5,380 properties in the region, most of which are private households and some typical Norwegian cabins. There are very few local businesses or industry connected to this transformer [102]. The transformer has a nominal capacity of 25 MW and since 2010, has experienced several events where the load on the transformer has exceeded this capacity, mostly during cold winter days.

In 2015, the mean consumption of the households connected to the transformer was 19,021 kWh/annum and the median was at 14,406 kWh/annum. The consumption of the houses peaks on average at 7 kW, while the median is 5 kW.[23]

[22] Consortium members: Aarhus University, Centre Suisse D'Electronique et de Microtechnique, University of Agder and Haute Ecole Specialisee de Suisse Occidentale, Fraunhofer IWES, Agder Energi Nett, SEIC Teledis, EnAlpin, Misurio, and Develco Products, Devoteam Solutions, Egde Consulting and Netplus.
[23] Information provided by AEN.

The transformer in Engene therefore builds the starting point for our analysis of peak-shaving in the distribution grid. To better understand the issues and the drivers for electricity demand, we will look in detail at the load on this transformer.

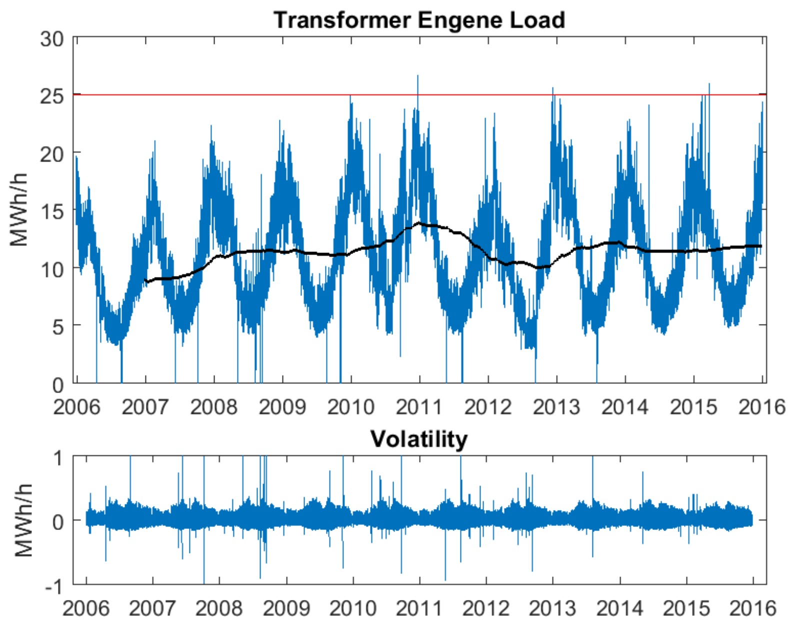

Figure 5-1: The load at the Engene Transformer: Upper plot – Hourly average load at Engene transformer from 2006 to 2015 in MW. Lower plot – Hourly volatility of the load at Engene transformer from 2006 to 2015 (Data source: Agder Energi Nett).

Figure 5-1 shows the hourly average load in MWh/h from 2006 until 2015, with the red horizontal line representing the maximum capacity of 25 MW. The data contains several values equal to zero. Those are actual measured data points rather than just measurement errors, why we did not exclude them from the data set. The reason for the zero values is maintenance during the summer months when total load is generally low and AEN has the possibility to shift the load to other transformers.

The seasonal fluctuation is clearly visible from the load curve. The average load overshoots the maximum capacity of 25 MW in nine hours within the ten-year period on four separate days: 24 Dec 2010, 12 Dec 2012, 24 Dec 2012 and 26 Mar 2015 – see Table 5-1. These peaks only reflect hourly averages, however, and instantaneous peaks within certain other hours could have gone above 25 MW. The most extreme overshoot was during Christmas 2010, when the transformer was operating during several hours on its limit. The most recent peak above 25 MW was in 2015.

	24.12.10	24.12.10	24.12.10	24.12.10	24.12.10	24.12.10	12.12.12	24.12.12	26.03.15
Hour of the day	11	12	15	16	17	18	9	17	11
Overshoot [MW]	0.28	0.2	0.04	0.52	1.68	0.28	0.6	0.04	1

Table 5-1: Date and absolute value of overshooting when hourly averaged load at Engene exceeded the nominal capacity of 25 MW and the transformer was at risk of an outage (Data source: Agder Energi Nett).

The yearly simple moving average (MA) of the hourly average load data in Engene is also plotted in the first figure. The MA indicates that during the winter 2010/2011 the load was extraordinary high and extraordinary low in the winter 2011/2012. One of the reasons is a slightly milder average temperature compared to the other years but very likely other factors contributed as well. Overall there seems to be only a small increase in the overall demand in Engene, bar a short jump in 2008.

Not only is absolute load fluctuating seasonally, also hourly volatility varies within the year and is higher during winter time as visible in the lower plot of Figure 5-1. However, volatility at the Engene transformer seems to have remained constant within the last ten years overall. If anything, volatility has slightly decreased over time.[24] One should also note that even though hourly volatility remained relatively constant throughout the ten-year period, all critical peaks have appeared after 2010.

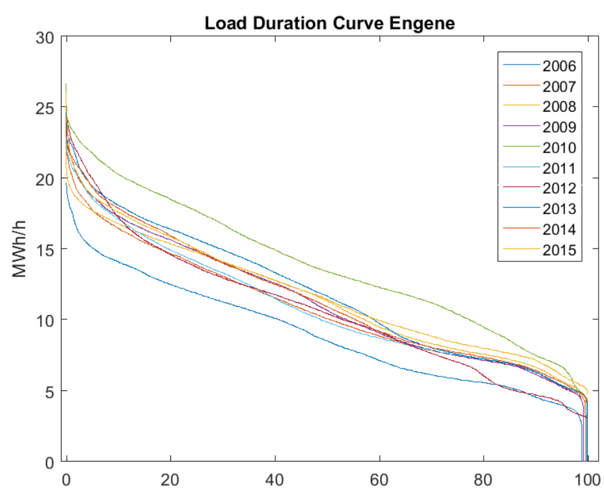

Figure 5-2: Load duration curve for the Engene transformer from 2006 to 2015. Values are sorted descending and plotted as a density function (Data source: Agder Energi Nett).

[24] To calculate volatility, zero load values were replaced by NaN (Not a Number) so it was possible to execute the calculation. The graph does not show the most extreme outliers due to the maximum and minimum values chosen for the y-axis.

The load duration curve in Figure 5-2 confirms that variation within the last ten years has not changed significantly. Beside 2010 and 2013 being slightly outside the norm, there is no visible change over time. In less than 0.5% of the hours of all the years, average hourly load in Engene was over 24 MWh/h. The load in Engene stays most of the time above 5 MWh/h but can jump to zero due to summer maintenance.

As mentioned above, the hourly average load data does not allow us to identify the absolute height of the peaks. As a consequence, we have to check higher resolution data to reveal the true instantaneous peaks during a peak hour. In Figure 5-3, we can see the load of the Engene transformer during the peak on March 26, 2015 in a resolution of 10 seconds. At 10 am the load reaches almost 28 MW and is therefore significantly higher than what we could see from the average hourly overshoots shown in Table 5-1. Within the following 45 minutes the load declined slowly until there was a big drop around 10:45 am, when the load was shifted to another transformer in the AEN network. AEN was in the lucky situation where not all the transformers connected to the Engene clusters were fully utilised. Hence, AEN could shift some of the load to these other transformers, so that a load level below 25 MW could be maintained.

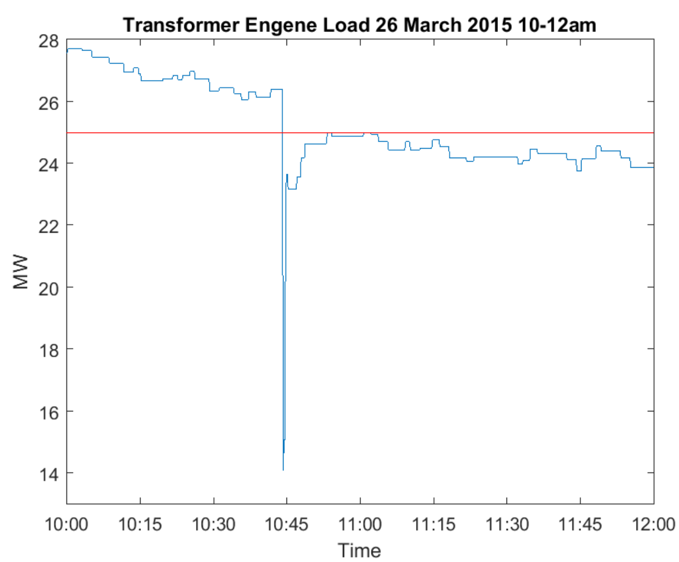

Figure 5-3: Ten second observations for the peak at the Engene transformer between 10 and 12 am on 26 Mar 2015 (Data source: Agder Energi Nett).

To understand peaks, it is important to assess why and when peaks occur. One well known driver of energy demand is temperature. This is valid for hot and cold regions. While in hot regions energy consumptions is highest during the summer month due to air conditioning, cold regions demand highest during winter due to heating. Accordingly, Norwegian residential energy consumption during the winter months increases a great deal. How well the load seasonal effects can be explained by temperature fluctuation is apparent from the first graph in Figure 5-4. The average daily load pattern of the Engene transformer is shown together with daily average temperature. The temperature Y-axis is reversed so that a fall in temperature is shown as an increase. The other two plots show the temperature and load for the months with critical peaks in 2010/2011 and 2015. Again, the same pattern can be observed: temperature drops and consequently load increases. One notes that a drop in temperature during periods of relatively warm weather seem to have a more drastic effect on load than during long periods of relative cold weather. The effect can be seen from comparing the second and the third plot. While in December 2010, temperatures were generally low and changes in temperature are relatively smooth with the load curve, temperatures in February and March 2011 were relatively warm and drops led to high peaks in consumption. Consumers seem to react more sensitively to drops in temperature when the weather is relatively warm. A phenomenon we all know: water feels cooler jumping in when the air temperature is high than when air temperature is low.

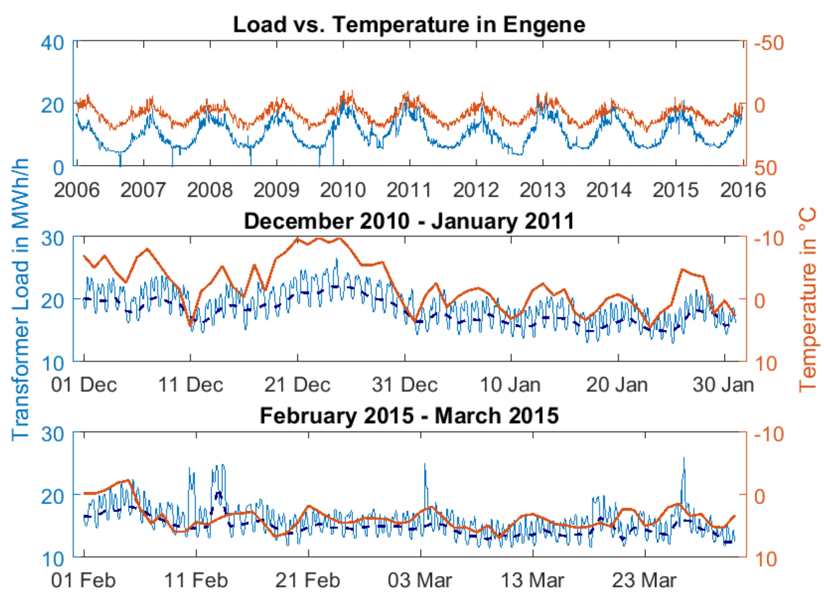

Figure 5-4: Load compared to temperature in Engene: Upper plot – hourly load at the Engene transformer and daily average temperature from 2006 to 2015 (axis reversed). Middle plot – hourly load at the Engene transformer and average daily temperature from 1 Dec 2010 to 30 Jan 2011 (axis reversed). Lower plot – as second plot but for time-period 1 Feb 2015 to 31 Mar 2015 (Data source: Agder Energi & eklima.no).

Temperature itself is not the only driver for electricity demand. Household load curves are to a large extent determined by when people are home and make most use of their devices by cooking, showering, charging their EV or other activities. To investigate further, Figure 5-5 shows load grouped by hour. In the upper graph, the distribution for each hour of AEN's distribution grid is plotted. Peaks usually happen around 9/10 am and 6/7 pm. The most unlikely values and therefore the highest peaks appear in the morning. For the Engene transformer, the same pattern is visible and shows a peak in the morning. The peaks appear around one hour later, 9-11 am and 7/8 pm and do not differ too much from each other. The highest peaks still appear in the morning though. This does not come as a surprise that the peaks appear at the times people get up and go to work or come home from work and have dinner.

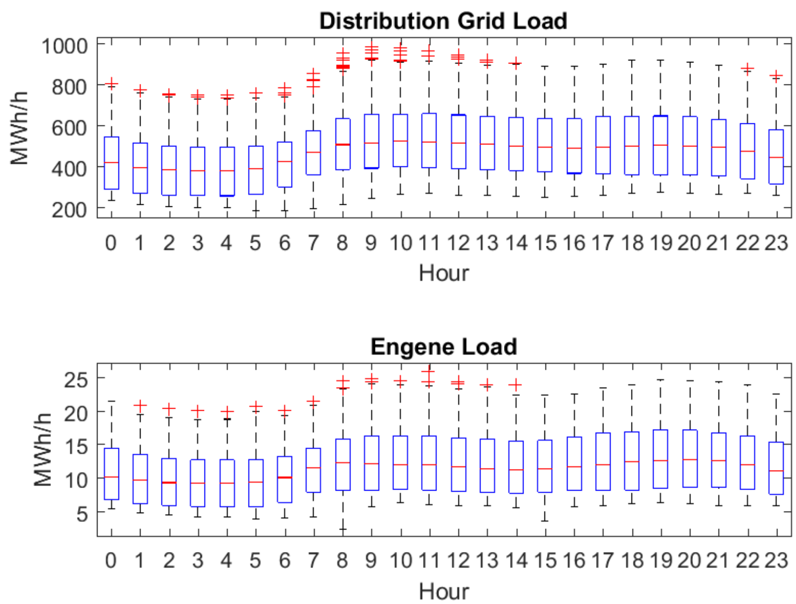

Figure 5-5: Hourly load distribution: Upper plot – boxplot of load for each hour of the distribution grid of Agder Energi Nett from 2013 to 2015. Lower plot – boxplot of load for each hour for the Engene transformer from 2013 to 2015. Whisker length is 1 x Interquartile Range (IQR) [25](Data source: Agder Energi Nett).

From a weekday perspective, the distribution grid load during workdays is generally higher than on weekends, likely due to local industry and businesses – see Figure 5-6. Within the workdays and weekends, the load seems relatively stable and does not fluctuate too much. The difference between weekend and workdays is almost not visible

[25] IQR is the difference between the third and the first quartile or in other words the difference between the 75th percentile and the 25th percentile. It contains the centre 50% of all observations and is unaffected by outliers [117]. By defining its factor, we can define the outliers.

for the Engene transformer. This makes sense since the load is mostly based on households and hardly consists of any industry or business consumers. Interestingly, both the distribution grid and the Engene cluster show their highest peak on a Thursday, which perhaps is a consequence of the Norwegian cabin culture. Some cabin owners have the possibility to pre-heat their properties via their smartphones and do so the day before they arrive for a weekend trip. Since the supplied region by AEN has many cabins (including Engene), the effect could be relatively strong.

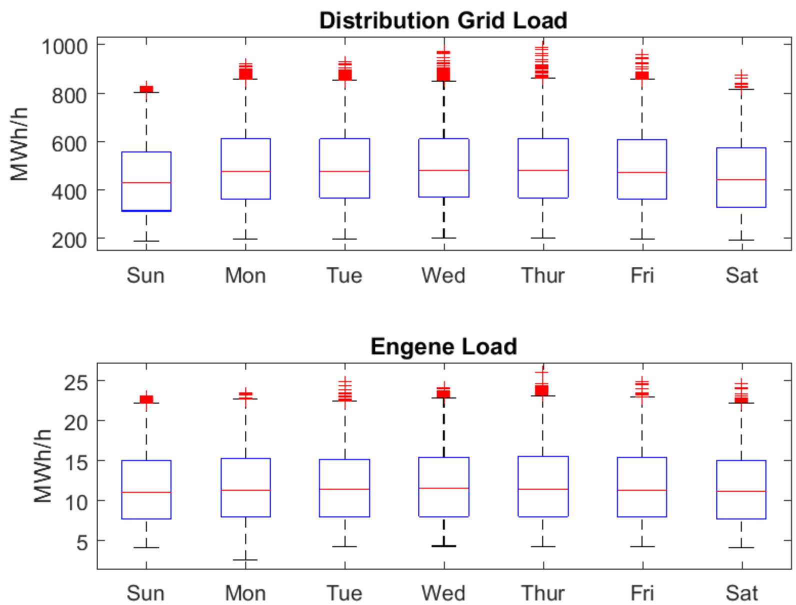

Figure 5-6: Daily load distribution: Upper plot – boxplot of load for each weekday of the distribution grid of Agder Energi Nett from 2013 to 2015. Lower plot – boxplot of load for each weekday at the Engene transformer from 2013 to 2015. Whisker length is 1 x IQR (Data source: Agder Energi Nett).

The seasonal fluctuations are apparent when load data is grouped by months as done in Figure 5-7. From a global perspective for AEN, the critical month of the year is clearly January, when the load in the distribution grid peaks at its highest. Load in December is typically lower than in January or February. For the Engene transformer we can see a different pattern. Even though load is generally highest in January, the highest peaks have occurred in March. Additionally, December and February can also see the transformer under high load. This is not consistent with the mean temperature data in Engene for the last three years. The coolest month on average was January, when in general load was the highest. The highest peaks appeared in March, when the average monthly minimum temperature was significantly higher.

The fact that peaks in Engene do not always appear at times when they appear in the overall distribution grid gives AEN the ability to shift power from one transformer to another if the physical circumstances allow for it.

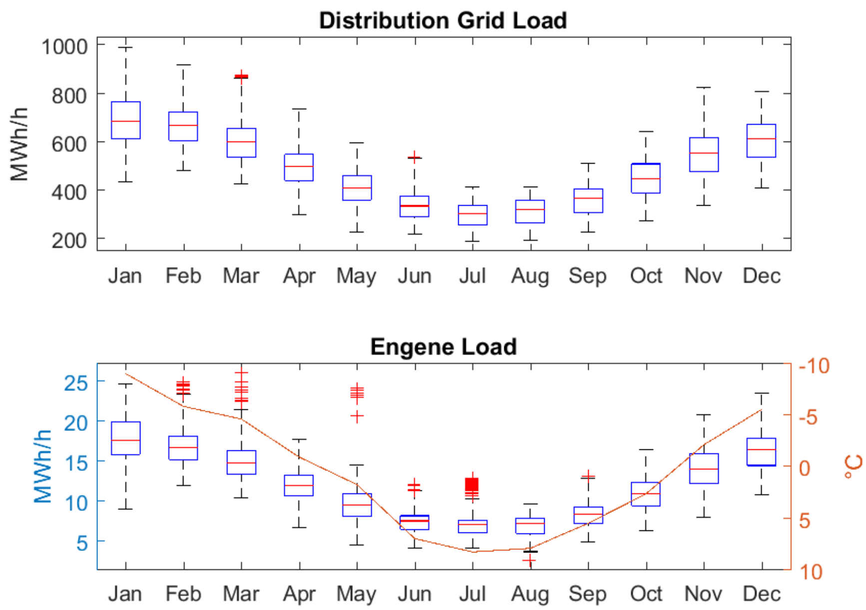

Figure 5-7: Monthly load distribution: Upper plot – boxplot of load for each month of the distribution grid of Agder Energi Nett from 2013 to 2015. Lower plot – boxplot of load for each month at the Engene transformer from 2013 to 2015. Whisker length is 1.8 x IQR. In addition, the lower graph also shows the inverse monthly minimum temperature in Engene (Data source: Agder Energi Nett & eklima.no).

Conclusively it can be said that a typical peak hour in the distribution grid of AEN would be on a Thursday between 9 and 11 am, at some point in January. In Engene, the typical peak hour would be on a Thursday between 9 and 11 am or between 7 and 9 pm, somewhere between December and March. Even though temperature is clearly one of the key drivers for power consumption, peaks cannot be explained purely by looking at absolute temperature values. The highest peaks do not necessarily appear during the coolest hours. Temperature seems to be of great importance for the prediction of peaks but the exact relation underlies further research and exceeds this paper's topic.

5.2 Characteristics of the Pilot

As mentioned, the SEMIAH project consists of two pilots, one in Switzerland and one in Norway. Both consist of 100 households modified for active and automated DR. The installed hardware and the type of installations that were defined for the two countries differ. Switzerland has four different types, some of which include rooftop solar and heat-pumps. In Norway, only two types were installed, boiler only and boiler and heating. The first setup shown in Figure 5-8 is boiler only and reflects 96 of the 100 households. The boiler is controlled by a smart plug and can cut the connection to the boiler. Boiler temperature is measured with a temperature sensor, which is connected to the outside of the outflow for hot water, just below the water mixer. The total load is measured with a pulse meter that reads the meter of the house.

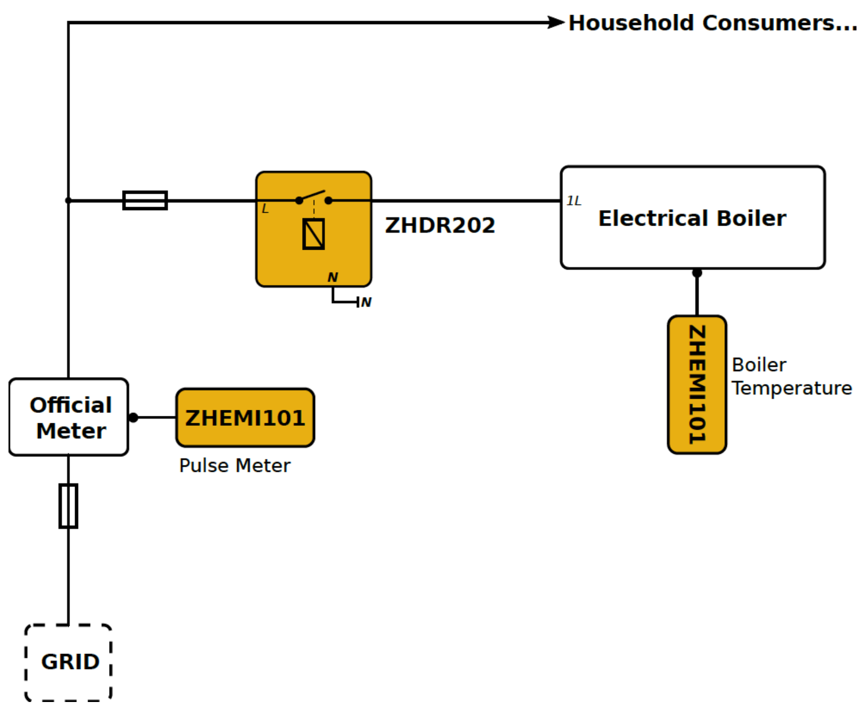

Figure 5-8: Technical scheme for boiler only installations in Norway.

The second type shown in Figure 5-9 contains boiler and heating. 4 out of the 100 households have this set up. The principle is the same as for the boiler only type but extended so heating can be measured and controlled. As is common in Norway, each room contains an individual panel heater and thermostat. To control the heating panels, each room was equipped with temperature sensors and smart plugs for the panel heaters. In addition, an outdoor temperature sensor was installed.

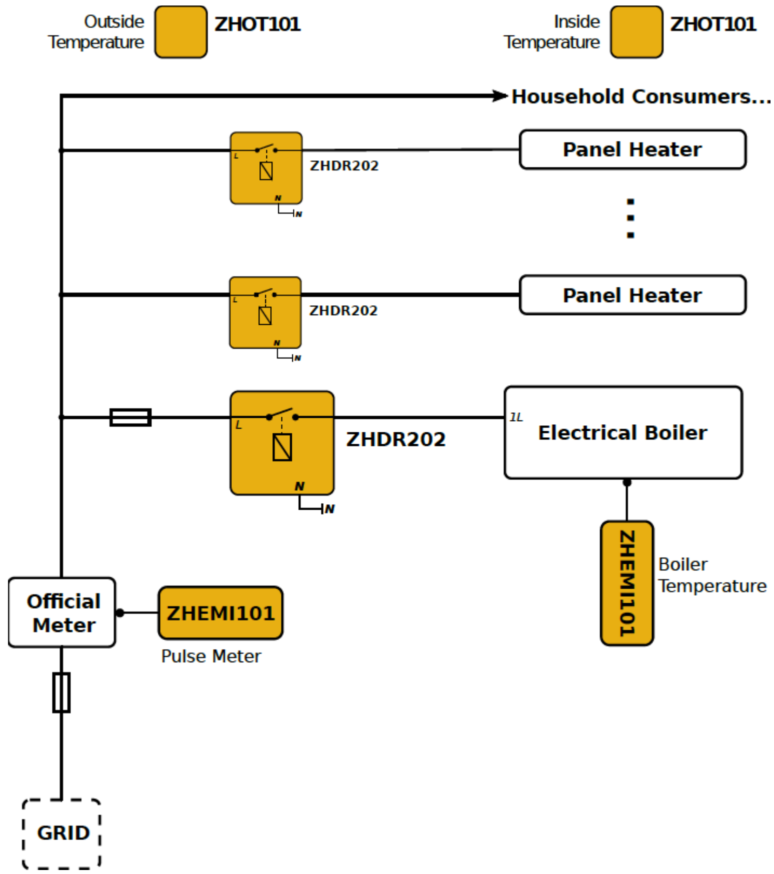

Figure 5-9: Technical scheme for boiler and heating installations in Norway.

For both installation types the data is sent via ZigBee[26] communication to a smart gateway. The gateway is connected to the SEMIAH software that collects the data to control the households. The connection from the gateway to the cloud is established via the normal mobile data network (GSM). As DR testing had not begun by the time we extracted our data, all the data used in this work is natural and has not manipulated by active DR [102].

5.3 Boiler Behaviour

A typical setup for a boiler is to keep the water in the tank heated between a specified temperature range, e.g. between 57°C and 60°C. In maintaining this temperature range, the electricity use typically runs in an on-off cycle where the heating element is turned

[26] ZigBee is a radio frequency technology for the transmission of small amounts of data, like Bluetooth or Z-Wave. The main purpose of ZigBee is for the data transmission in the near range for home automatization and IoT [118].

on to heat the water up to the specified upper temperature (e.g. 60ºC) and turned off when this temperature is reached. The insulation in the water tank keeps the water warm enough for a few hours until it reaches the lower temperature (e.g. 57ºC), when the boiler is turned on again and the cycle continues. This low temperature can occur through the water slowly cooling in the tank or suddenly if a large amount of hot water is drawn, for example due to taking a shower. The new water that replaces the drawn hot water is cold, so instantly reduces the temperature in the water tank. When a household runs out of hot water, this is when hot water has been drawn out of the water tank at such a rate as to not give the boiler enough time to heat the new water up to a sufficient temperature.

Figure 5-10 shows the behaviour of the boiler in House 200 on a randomly selected day – November 20, 2016. The specified temperature range for this boiler is 57-60ºC, as indicated by the two dotted black horizontal lines. From 00:00 you can see the boiler is not turned on and no water is being drawn as the temperature is slowly decreasing. When the temperature reaches just below 57ºC at around 06:00, the boiler is turned on and the water is heated back to around 60ºC. A slow decline in temperature to 57ºC follows until turning on at around 13:00, again indicating little or no hot water being drawn during the preceding period. Then at around 16:00 there is a dramatic drop in temperature, indicating the drawing of hot water, most likely as the residents arrive home. To reheat the new cold water that replaced the drawn hot water, the boiler is required to be on for around 1 hour before it reaches the desired temperature of around 60ºC.

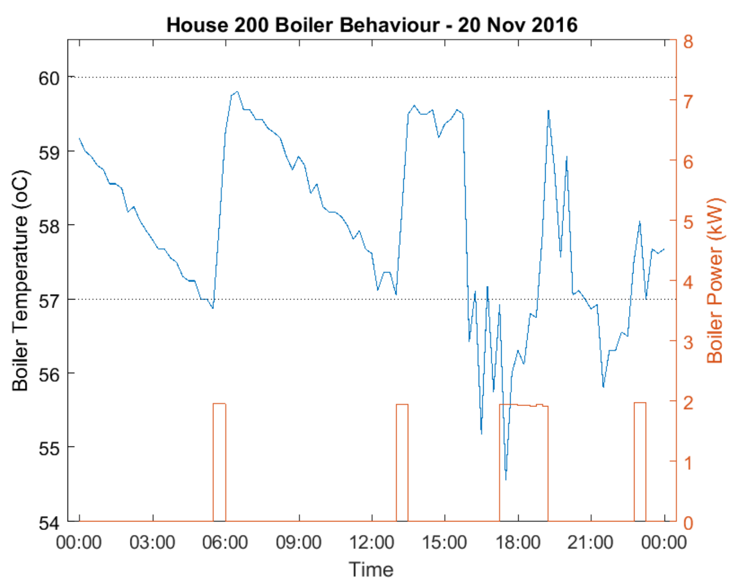

Figure 5-10: Household 200 boiler temperature and boiler power on 20 Nov 2016 (Data source: SEMIAH pilot).

The setup of a boiler from house to house can vary significantly. The main elements that can differ are insulation level, temperature range, heating element efficiency and water tank size. Better insulation will keep the water warmer for longer and will require power less frequently, making it a better energy storage device and more flexible in use. A tighter temperature range, e.g. 57-58ºC as opposed to 55-60ºC, will require power more frequently and is therefore less flexible in use. A temperature range with a higher operating temperature, e.g. 58-60ºC as opposed to 48-50ºC, will require power more frequently and require more power over time i.e. energy to maintain the desired temperature range. A more energy efficient heating element will require less power over time to heat the water and therefore is more flexible in use. Finally, a larger water tank will be able to support more hot water demand and therefore can provide more energy storage in the water tank, however will require more power over time to keep the larger amount of water heated continually.

Table 5-2 presents a summary of the boiler specifications across the 22 selected households. As will be explained in our description of the model in the next chapter, specifically in section 6.2.1, only 22 of the 100 households could be used in our study. For specific data on each boiler in each household, please see Appendix B. The average cycle time represents the amount of time between when the boiler turns off at the upper temperature, to when it turns back on when it reaches the lower temperature. This cycle refers only to when no water has been drawn during this time, i.e. when the boiler is laying idle, e.g. when not used during the night, as in Figure 5-10. This time period therefore gives the best impression of the insulation offered by the boiler. The average cooling rate during this cycle time is calculated by dividing the number of degrees centigrade of the fall in temperature by the average cycle time.

	Tank size (litres)	**Idle Low Temp. (oC)**	**Idle High Temp. (oC)**	**Range (oC)**	**Avg. Cycle Time (Hours)**	**Avg. Cooling Rate (oC/hr)**
Min	198	42	45	0.5	1.20	0.13
Max	198	67	73	16	9	4.25
Mean	198	54.9	58.8	3.9	4.07	0.98

Table 5-2: Boiler specifications for the 22 selected households (Data source: SEMIAH pilot).

All 22 selected households had 198 litre boilers. The mean temperature range for the 22 boilers is 54.9ºC to 58.8ºC but you can see in the minimum and maximum values that the individual temperature settings can vary hugely. Indeed, the range can also vary hugely between maintaining a temperature range of just 0.5ºC to a range of 16ºC. Likewise, the implied insulation of each boiler through the average cooling rate can vary significantly between households.

For the optimisation models that we present in chapter 6, boiler specifications beyond their nominal power rating are not required. However, if future DR models for controlling boilers attempt to model their behaviour, some issues need to be considered. In a smart grid community of many tens of thousands of households, gathering and modelling this information for individual households may prove difficult. In this light, some standardisation of boiler installation, water tank sizes and/or settings would help. The typical end consumer is unlikely to know or even care what size his boiler tank is or the temperature range the boiler is set to – as long it provides cost effective hot water, then most users will be happy.

Additionally, to note, the average upper and lower temperatures in the pilot households are very high for what is generally required when using hot water for showers and washing. A typical temperature for taking a shower is between 40-45^{o}C and in some countries there are health regulations, such as the Health and Safety Executive in the UK, which suggest temperatures above 44^{o}C have a risk of scalding skin [103]. The high temperatures in the pilot households will likely be due to Norwegian building regulations that suggest that the temperature required to avoid legionella bacteria is 60^{o}C [104].

The data shown in Table 5-2 and in Appendix B was obtained by selecting a number of time periods in order to ascertain an approximate idea of the behaviour of each individual boiler. There are some external factors which could affect the performance of the boilers, such as the indoor temperature of the room the boiler is in or the temperature of the cold water being heated on the day of the observation. We did not have indoor temperature information or the temperature of the cold water but assume that the cold water temperature is similar for each household and is linked to outdoor temperature. We therefore chose time periods for each household that were within a few days of each other – all at the beginning of December 2016.

5.4 Individual Household Load

As one of the first houses connected in Norway, House 200 (H200) provides good data quality from June 22, 2016. Although in the optimisation in the following chapter we only model an eight-week period at the end of the year – November 14, 2016 to January 8, 2017 – we can still analyse a longer period for this individual household since we have the data.

House 200 is a typical boiler only setup – with boiler temperature, boiler power and meter power. We also know that the boiler has a peak power of 1.95 kW and a water capacity of 198 litres. This represents very close to the mean boiler peak power of 2.01 kW across the 22 selected households. The idle temperatures with which the boiler oscillates when no water has been drawn is 57^{o}C and 60^{o}C, and this cycle of heating to 60^{o}C and cooling to 57^{o}C takes around 4 hours, representing an approximate cooling rate of 0.75^{o}C per hour. These numbers are again comparable with the mean values for the 22 selected households – temperature range of 54.9^{o}C to 58.8^{o}C, cycle time of 4.07 hours and cooling rate of 0.98^{o}C. Overall therefore, House 200 represents a very good example of a boiler only house to be analysed individually.

Figure 5-11 shows the meter power for the whole household in blue and the boiler power in red, in hourly intervals from June 22, 2016 until the end of the testing period January 8, 2017. As you can see, the total power for the household varies quite dramatically from hour to hour and day to day. The lowest value was 0 kW on several occasions and the highest was 11.2 kW at 18:00 on November 21, 2016. The highest peak looking at higher resolution of 15 minutes is 11.5 kW at 18:00 on November 24, 2016. The mean value is 1.88 kW and a standard deviation of 1.53 kW. With a maximum peak, which is over 5 times higher than the mean, this shows how much extra resources on the grid are required just to support occasional usage periods way above the average power level. The boiler power represents a steady on or off consumption of 1.95 kW which if turned off at the right moment, could help reduce the peak power of the household.

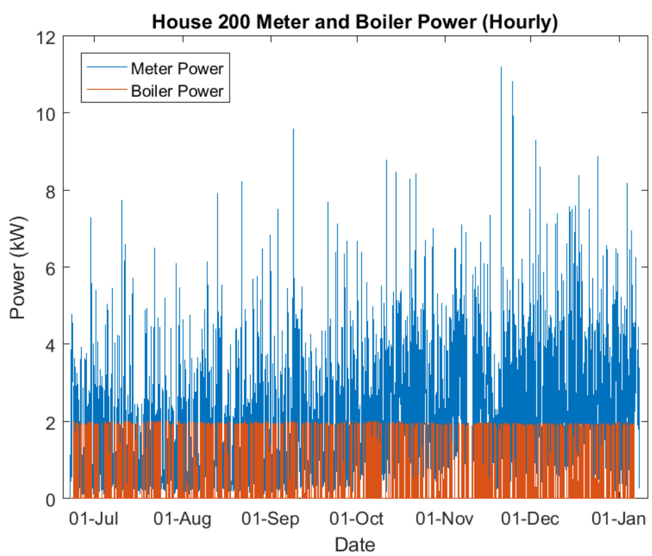

Figure 5-11: Hourly meter and boiler power for Household 200 from 22 Jun 2016 to 8 Jan 2017 (Data source: SEMIAH pilot).

Looking more closely at peak of 11.5 kW which occurred at 18:00 on November 24, 2016, Figure 5-12 shows the load profile of house 200 for that day. With a higher resolution of readings every 15 minutes, we see in more detail when the peaks occurred. By subtracting the boiler power from the meter power at each time interval, the orange line shows how the peaks could have been reduced if the boiler was turned off. Indeed, for nearly all the peaks around 18:00, turning the boiler off would have reduced the peak significantly. If the boiler could have been pre-heated between 16:00-17:00, when the non-boiler consumption was relatively low at around 3-5 kW, it may have been possible to keep the boiler off over the peak period that followed – depending on the total water demanded.

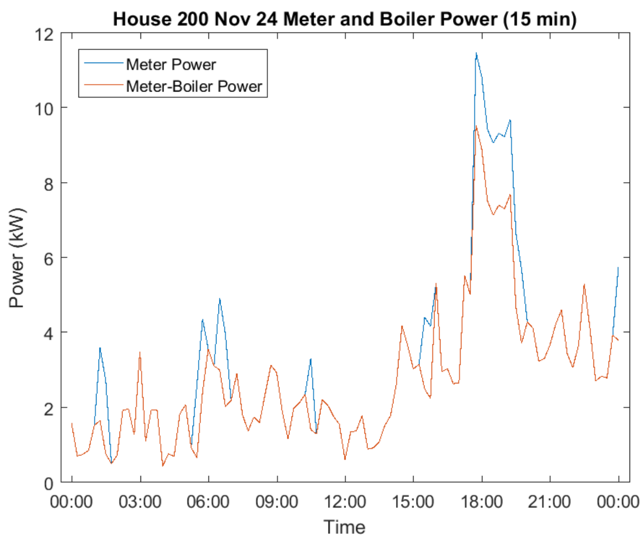

Figure 5-12: Fifteen-minute meter and boiler power for household 200 on 20 Nov 2016 (Data source: SEMIAH pilot).

These graphs for House 200 merely give a graphical impression what the affect could be if the boiler was controlled. A far more precise modelling of whether this is possible will be covered in our optimisation of all 22 households in chapter 6.

5.5 Aggregate Loads

In aggregating the loads of the 22 households to form the pilot community, we begin to see the potential from aggregation. Figure 5-13 shows the total load for the community for the 8-week testing period – November 14, 2016 to January 8, 2017. The simple 1-day moving average of the aggregate load is the upper line in red and the aggregate load minus the aggregated boiler load is the lower line in yellow. Note there is a small gap in the moving average curves around December 5 – this is due to a short data outage of meter readings. The trend is clearly upward moving from start to finish – as expected moving into the typically colder months of December and January. The highest peaks are also found in the later months – the two highest of 103.9 kW and 98.7 kW between 18-19:00 on January 5 and third highest of 98.5 kW between 17-18:00 on December 14.

The meter load minus boiler load moving average curve nicely shows the amount the boilers account for total aggregate load in the community. Throughout the period, you can see the boiler represents several kW of power that could be controlled to reduce peaks in critical periods. The lower plot of Figure 5-13 shows only the aggregated boiler load. This shows how the boiler load remains fairly constant throughout the testing period, despite the meter load shown in the upper graph increasing. This perhaps suggests the seasonal effects of boiler load are not that significant. The increase in total load is likely therefore due to increases in heating consumption.

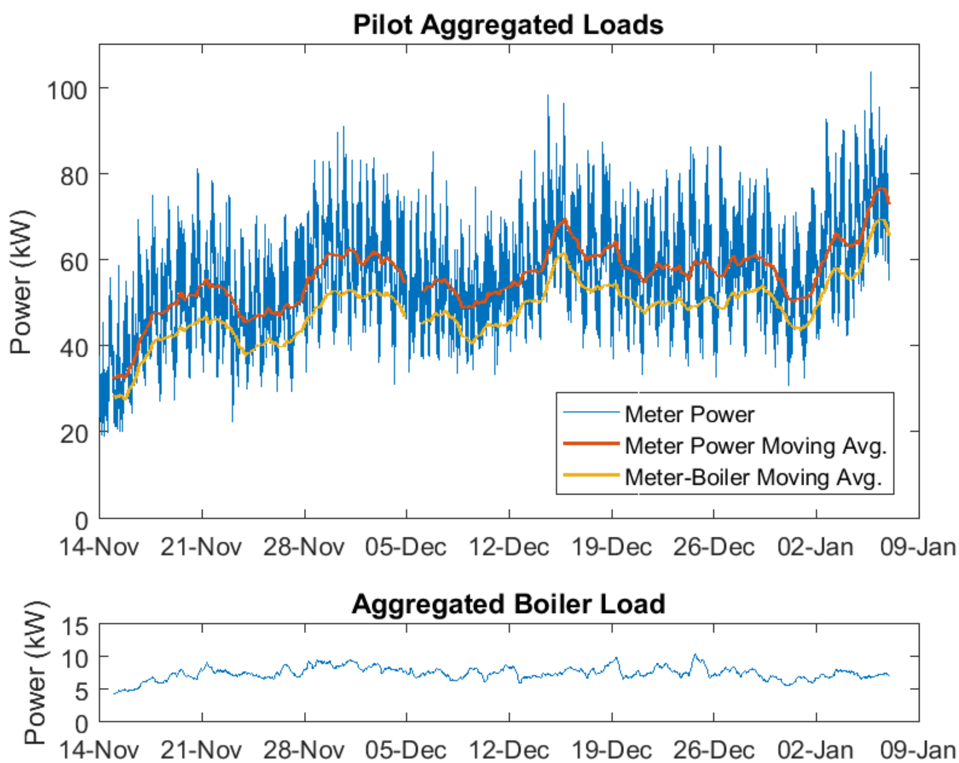

Figure 5-13: Pilot Aggregated Loads: Upper plot: Aggregated meter power and 1-day moving average for aggregated meter power and aggregated meter power with boiler power subtracted. Lower plot: 1-day moving average for aggregated boiler power (Data source: SEMIAH pilot).

Taking a specific look at the highest two peaks, we can see in Figure 5-14 how if it were possible to turn off some or all of the boilers, this could have reduced the peaks around this time significantly. Particularly for the single highest peak of 103.9 kW at 18:30, where the respective boiler power was 16.3 kW, representing a potential peak reduction of 16%.

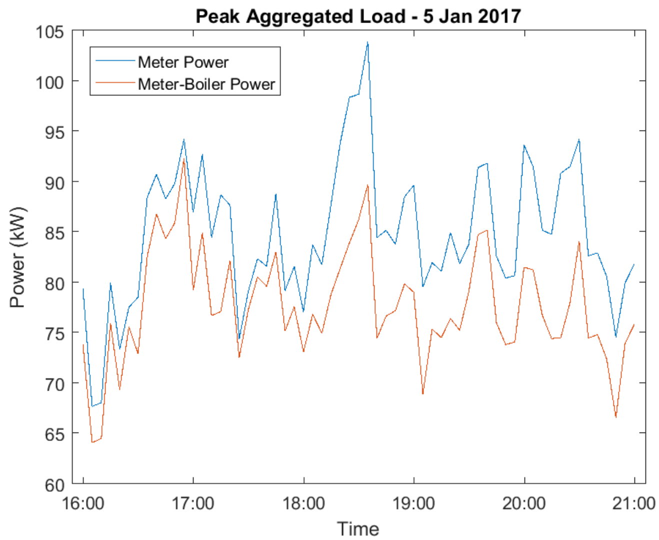

Figure 5-14: Aggregated meter power and aggregated meter power with boiler power subtracted on 5 Jan 2017 (Data source: SEMIAH pilot).

Figure 5-15 shows the hourly boxplot for the pilot aggregate meter load and the Engene transformer for the same period for comparison. With the pilot, we find the highest usage at hours 17 and 18, with the highest outlying peaks coming from the 18 hour (i.e. 18:00-19:00). Indeed, as identified in Figure 5-14, the highest single peak for the pilot was recorded at 18:30. These same early evening peaks are also found at the Engene transformer during the testing period. Note however the Engene peaks are slightly earlier than that observed for the 10-year data series for the Engene transformer in Figure 5-5, where load is concentrated slightly more around hours 19 and 20. This is likely due to our period only covering late autumn and winter months, where the days get darker and colder earlier, requiring electricity for heat and lighting earlier.

The general morning peak is observed at hour 7 for the pilot, with some higher outliers at 8, but is spread between 8 to 11 at the Engene transformer. This could be explained by the fact that the pilot consists of only residential homes whereas the Engene transformer will include some businesses. Therefore, after consuming electricity at home before work, they will arrive at work a little later and start consuming at their workplace.

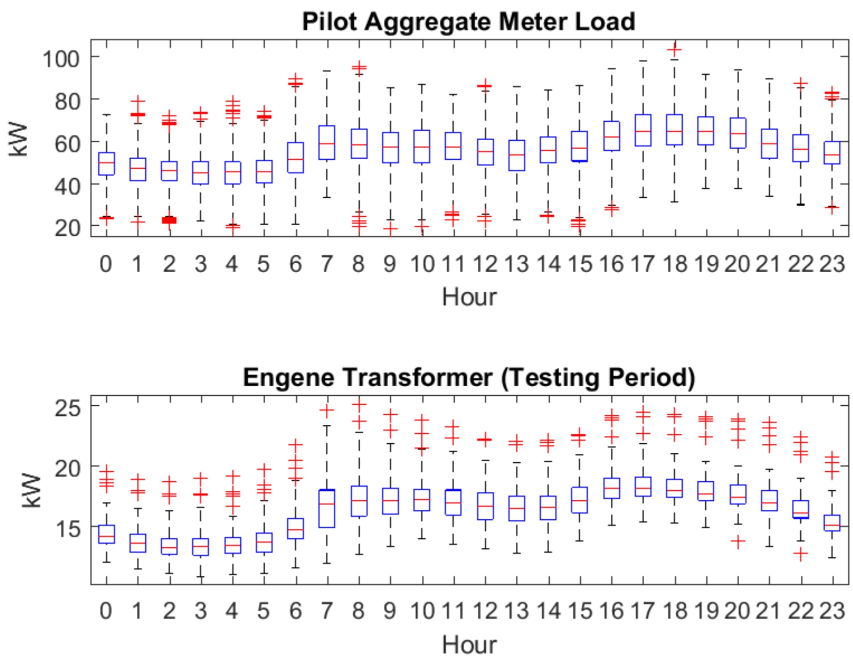

Figure 5-15: Pilot hourly load distribution: Upper plot – boxplot of load for each hour for the aggregated 22 households from 14 Nov 2016 to 8 Jan 2017. Lower plot – boxplot of load for each hour at the Engene transformer from 14 Nov 2016 to 8 Jan 2017. Whisker length is 1.9 x IQR (Data source: SEMIAH pilot).

The pilot peak at hour 7 is consistent with the Norway pilot boiler peaks shown in Figure 5-16, showing that boilers should be contributing to this peak and is consistent with expected water demand for a morning hot shower. Additionally, we see many higher outliers at hour 6 for the boiler. This could be due to the boiler being set on a timer so that hot water is guaranteed for the morning showers.

We have also included the Swiss pilot data in Figure 5-16 for comparison. This data set comprises of 25 households all with the same boiler only setup as described for the Norwegian pilot in section 5.2. Each selected household has good data quality and the data selected is the same testing period of November 14, 2016 to January 8, 2017. Comparing with Norway, we also see the morning peak at hour 7. However, there is a huge peak at hour 22, which is due to the two-tariff system in Switzerland. Households are typically exposed to a standard day tariff and a cheaper night tariff, so they are incentivised to shift load to the night time. This helps to reduce some of the grid load during the day. Many boilers can be timed so that they start heating after 22:00, when the night tariff starts. This also explains why there are an unusual number of lower outliers at hour 22 – these are the houses that have not set a timer on the boiler to turn on at 22:00 and therefore have a 'normal', much lower level of boiler consumption at that time. This example nicely shows the effect ToU tariffs can have. On the one hand, they help to reduce consumption during one period of the day but on the other they can create new peaks. In Switzerland, the new peaks are not an issue since grid capacity is typically large enough.

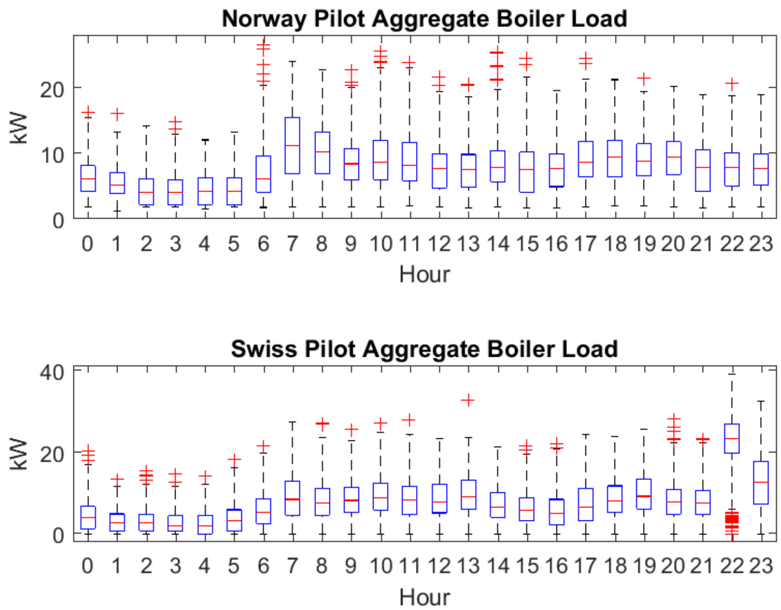

Figure 5-16: Pilot hourly load distribution by country: Upper plot – boxplot of boiler load for each hour for the 22 aggregated households in Norway from 14 Nov 2016 to 8 Jan 2017. Lower plot – boxplot of load for each hour for 25 selected aggregated households in Switzerland. Whisker length is 2 x IQR (Data source: SEMIAH pilot).

Figure 5-17 shows daily boxplots for the pilot aggregate meter load, the Engene transformer and the pilot aggregate boiler load. Interestingly for the pilot meter load, as with the 10-year series for the Engene transformer, we see a slight concentration and the highest outliers on Thursdays. As mentioned previously, and particularly now we are considering only residential homes during colder months, this could be explained by the process of remotely pre-heating one's cabin on a Thursday before arriving for a weekend trip. Looking at the Engene transformer for the testing period, however, does not necessarily show a concentration on Thursday. The highest outliers are seen on Tuesdays and Mondays, and Monday, Tuesday and Wednesday all show higher median values.

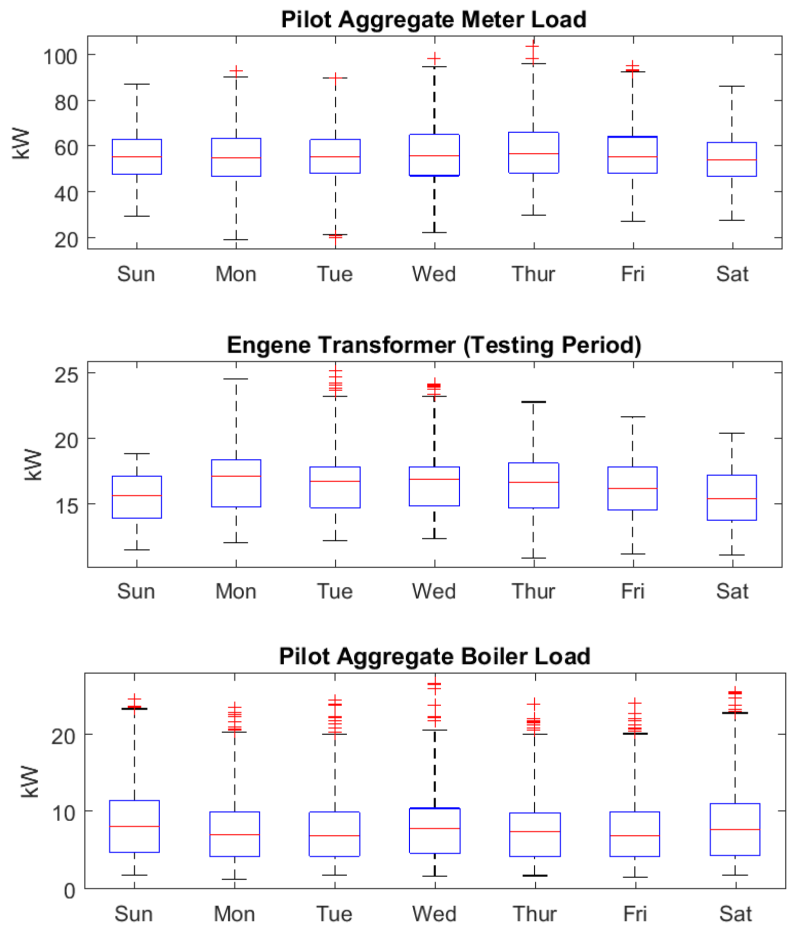

Figure 5-17: Pilot daily load by device: Upper plot – boxplot of load for each weekday for the 22 aggregated households from 14 Nov 2016 to 8 Jan 2017. Middle plot – boxplot of load for each weekday at the Engene transformer from 14 Nov 2016 to 8 Jan 2017. Lower plot – boxplot of boiler load for each weekday for the 22 aggregated households from 14 Nov 2016 to 8 Jan 2017. Whisker length is 1.8 x IQR (Data source: SEMIAH pilot).

For the pilot aggregate boiler load shown in Figure 5-17, we see a concentration of higher values on Saturdays and Sundays. This is consistent with residents spending more time at home during the weekend and therefore using more hot water for all purposes. As some of the homes in the pilot set are cabins/holiday homes, hot water usage is also expected to be concentrated over the weekend when these homes are inhabited most. Other than this, usage throughout the weekdays is relatively stable and high outliers are distributed quite evenly, meaning the highest aggregate boiler peaks can be seen on any day of the week.

Finally, in Figure 5-18 we see how the aggregate meter load over the whole period compares with that of the Engene transformer and the temperature in the Engene region. In the top graph, the 1-day simple moving average for the Engene transformer is plotted against the raw pilot aggregate load. As we can see, the Engene transformer follows a very similar path to that of the pilot. This gives us confidence that the pilot represents a good proxy for the Engene transformer.

The lower graph plots the reverse temperature in the Engene region against the pilot aggregate meter load. The pilot load seems to follow temperature relatively well, however as identified previously, decreases in temperature seem to cause a much larger shift than increases. If we consider heating, and to some extent hot water, as the main driver of shifts in electricity consumption in reaction to temperature changes, residents are less likely to turn their heating down immediately after a cold spell ends than they are to turn their heating immediately up when a cold spell starts. This is likely due to a lower tolerance to cold indoor temperatures than warm indoor temperatures.

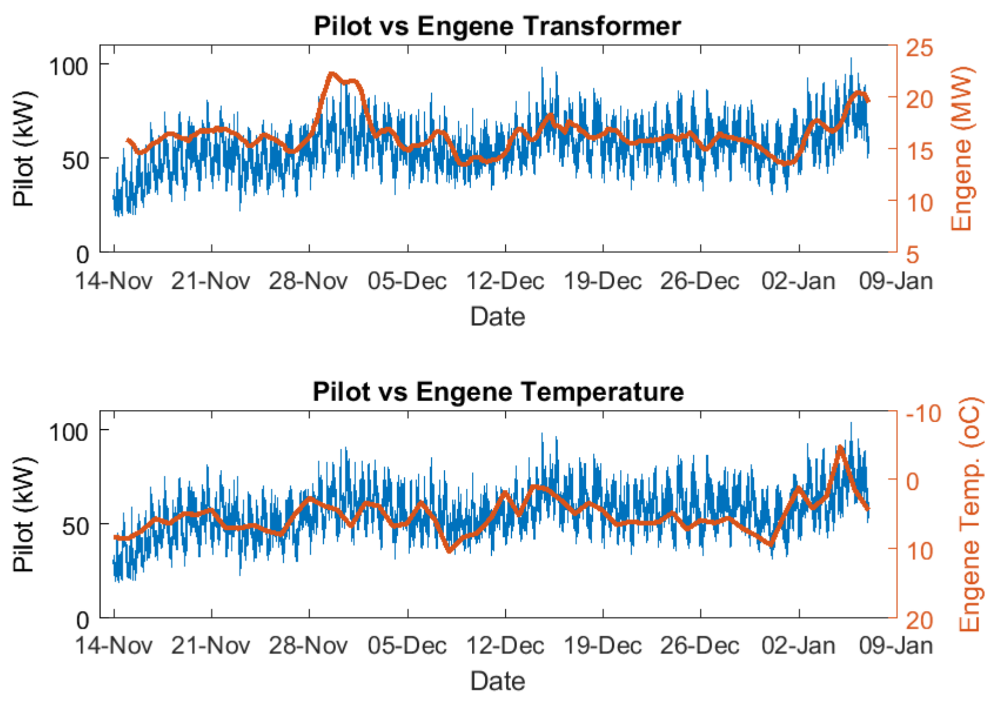

Figure 5-18: Pilot load against temperature: Upper plot – aggregated meter power and hourly load at the Engene transformer. Lower plot – aggregated meter power and daily average temperature (axis reversed) (Data source: SEMIAH pilot).

6. Market Simulation

6.1 Market Models

6.1.1 DSO Model

The first market model in our analysis is based on active DR controlled by the DSO. To be able to access the flexibility of the households either all or a critical group of the DSO's customers have smart devices installed. They allow the DSO to measure relevant data and to control required devices, in our case hot water boilers. The DSO will then use the flexibility to minimise his costs, which are consisting of operation costs and investment costs – see Figure 6-1. The amount of energy consumed by the households will not be changed. All that will be done is shifting load in time.

The households set their comfort settings, which are hard constraints for the DSO. Even though a household is committed to DR, his comfort settings can never be violated. Comfort settings can for instance be room temperature constraints or blocked time slots when demand is unchangeable. In the model, households are just providing their flexibility without any obvious personal benefit. Realistically, households should profit somehow. Otherwise it will be difficult to attract them to a DR scheme.

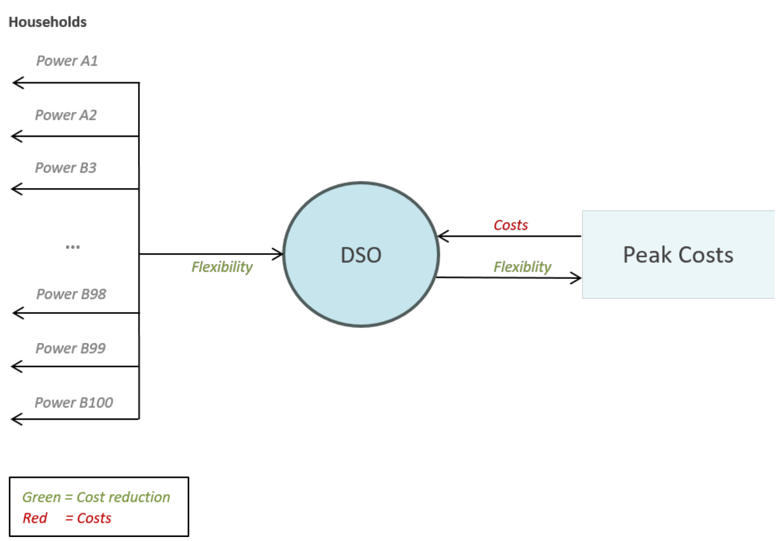

Figure 6-1: The DSO Model used for the simulation is a simple peak costs optimisation. The DSO controls the household flexibility directly.

The operation costs in Norway that can be influenced by DR are mostly the grid tariff payed to the TSO. The main driver for those costs is the consumption during the peak hour of the year in the transmission grid over five years (see section 2.5). Since it is difficult to predict this particular hour and due to the determination over several years, it is hard to optimise these costs, at least in the short term. The design of this tariff also means that the DSO tries to minimise its global peaks at certain access points to the transmission grid, so the maximum peak will be as low as possible.

The investment costs are mainly driven by capacity. Hence, the DSO can use flexibility to shave peaks and avoid congestion. This will increase the efficiency of the grid usage and allow the DSO to avoid or postpone investments. This problem is potentially more local than operational costs. Consequently, the DSO could be more focused on critical sub clusters of his grid rather than global peaks. In the optimisations of this paper, we look at the data for the particular transformer in Engene. Thus, the optimisation will focus on local peak shaving and see if it is possible to keep the load below a certain level. The short-term perspective such as operation or maintenance costs are not considered in our model.

6.1.2 Aggregator Model

The second market model that we look at is with a third-party aggregator shown in Figure 6-2. The aggregator is supplying the electricity for the households. Instead of the DSO, the aggregator is now controlling the DR infrastructure and shifting consumption over time. Differently to the model before, the aggregator can now exploit the household flexibility at different markets and generate income from this activity. Current regulation in liberalised electricity markets encourages a separation of grid companies from energy suppliers and similar activities. Thus, it is unlikely that a DSO would take on an aggregator role.

Firstly, the aggregator can exploit the flexibility on the day-ahead and intraday markets so that he can buy electricity when it is cheapest. Secondly, the aggregator can sell the flexibility on the ancillary services markets to help stabilise the grid. Thirdly, the DSO offers to purchase the flexibility from the aggregator. In our model, we assume the DSO's aim is to keep their grid load under a certain level. Therefore, the DSO will pay a certain amount to the aggregator to prevent peaks above an agreed level in a particular grid cluster (here Engene). No matter where the aggregator sells its flexibility to, it will also be partly used to minimise balancing costs, as described in section 2.4

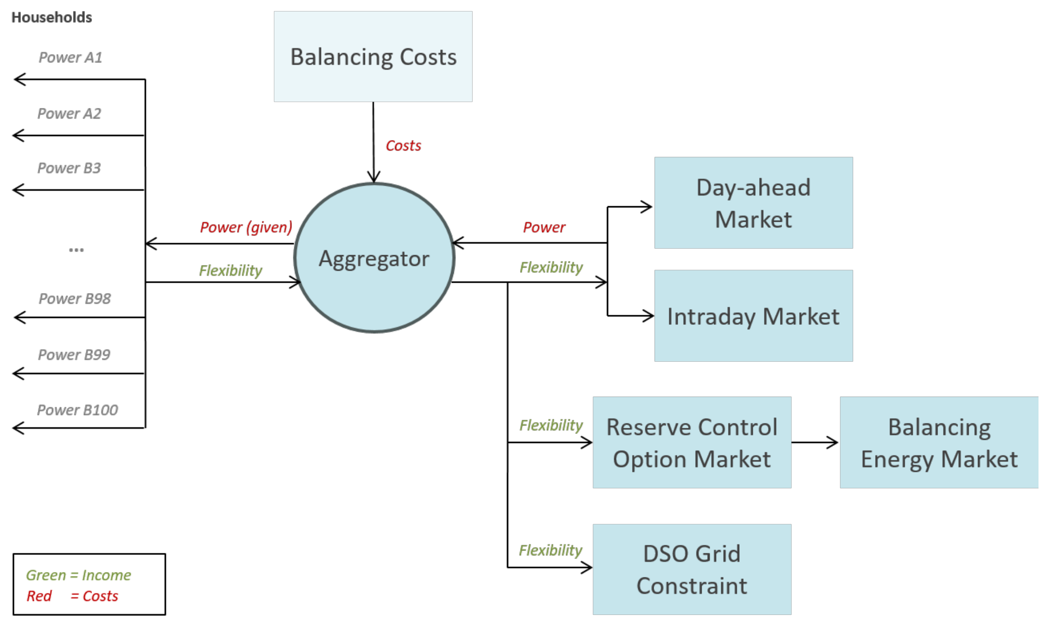

Figure 6-2: The Aggregator Model exploits flexibility on four different markets. Household flexibility is controlled by a third-party, the so-called aggregator.

Again, the benefits for the households will be ignored and their total energy consumed seen as constant. Comfort settings are again hard constraints for the aggregator and cannot be violated. The real business model, with household tariffs and pricing systems, will not flow into this analysis. Thus, even though the aggregator is maximising profits, the model minimises his purchase costs, which leads to the same outcome.

6.2 Data

6.2.1 Household Data

As mentioned in chapter 5, there are a total of 100 households connected to the Norwegian SEMIAH pilot – 4 with smart heating and boilers, and 96 with smart boilers only. When investigating the data quality of each household we found issues such as large gaps or recording errors, so we were not able to include all households. We also wanted to use a longer period for our optimisation, however, although the first household was connected on June 22 and many more were connected before our starting point of November 14, 2016, we found the period with the best data quality and sufficient number of houses was the one selected – November 14, 2016 to January 8, 2017.

After lengthy analysis in all connected households, we could select 22 households. Of these 22, only 1 was a smart heating and boiler household. With a sample of one household, we therefore felt we should not run a separate optimisation just for heating. We therefore focused purely on the optimisation of boiler consumption.

For each household, we required the meter power and the boiler power. The meter power provided the total electricity consumption of each household, which when aggregated would provide some peak periods of load to be shaved. When subtracting the boiler power from the meter power, a residual amount is calculated – the residual power. This residual amount of energy is consumed by appliances other than the controllable boiler and therefore cannot be optimised and is fixed. The boiler power is variable and when aggregated provides the total amount of energy that can be optimally procured on the wholesale market and/or offered in the ancillary service market. The boiler power is also used to model a typical load path for each household, as described in detail in section 6.3.

The peak for aggregated meter power is 96 kW at 18:30 on January 5, 2017. This is at a 15-minute resolution, the same used in our optimisation. On a 5-minute resolution, the peak was 104 kW, as shown in Figure 5-14 in section 5.5. The peak for the residual power is 88 kW at 15:45 on January 5, 2017, on a 15-minute resolution. Our global peak reduction is therefore limited to this peak, as this is the highest peak where boiler power is equal to zero.

Figure 6-3 shows the time series of daily aggregated meter power during the testing period, with min, max and mean daily values, with solid lines representing 15-minute resolution values and dotted lines for the 5-minute resolution values. The dips around December 5 and January 7 are where there was a loss in connection and limited or no recorded meter data.

Figure 6-4 shows the boxplot of daily boiler consumption for each household. We can see that daily consumption in each household varies quite dramatically. As identified in section 5.3, all boilers have the same water capacity of 198 litres however they all have quite different operational settings, e.g. temperature range. The largest consumer H264 in fact has a typical temperature range of between 54-58^{o}C, so this high consumption is likely due to a large family inhabiting the house and/or a large demand for hot water for some other reason. The next three highest users however – H289, H267 and H280 – maintain three of the highest temperature ranges – 1st, 2nd and 5th respectively – with H289 with a range of 67-73^{o}C. Without knowing each household's physical water demand, this still shows an interesting insight as to one of the other drivers of boiler consumption other than pure water demand. All things remaining equal, if the temperature ranges of these boilers were lower, the total consumption of energy would likely be lower.

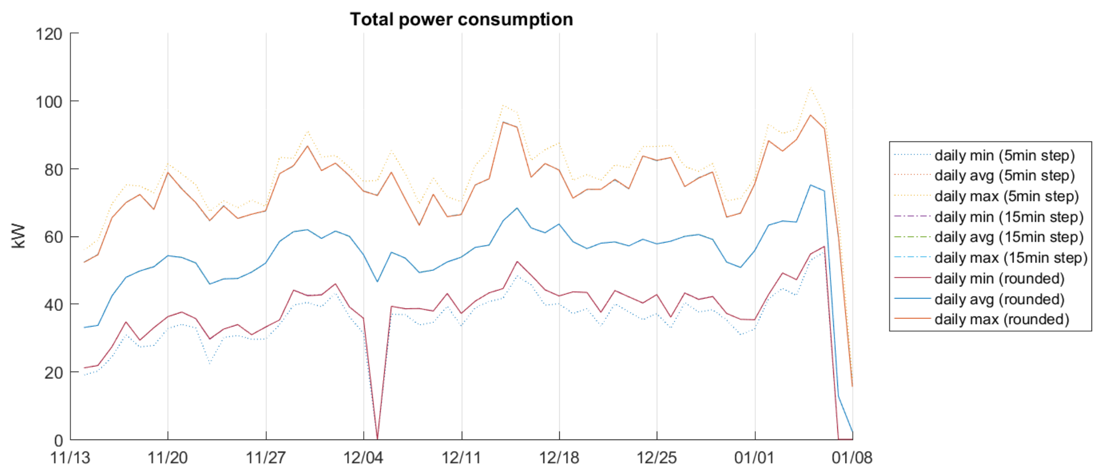

Figure 6-3: Daily load for the aggregated 22 households from 14 Nov 2016 to 8 Jan 2017 (Data source: SEMIAH pilot).

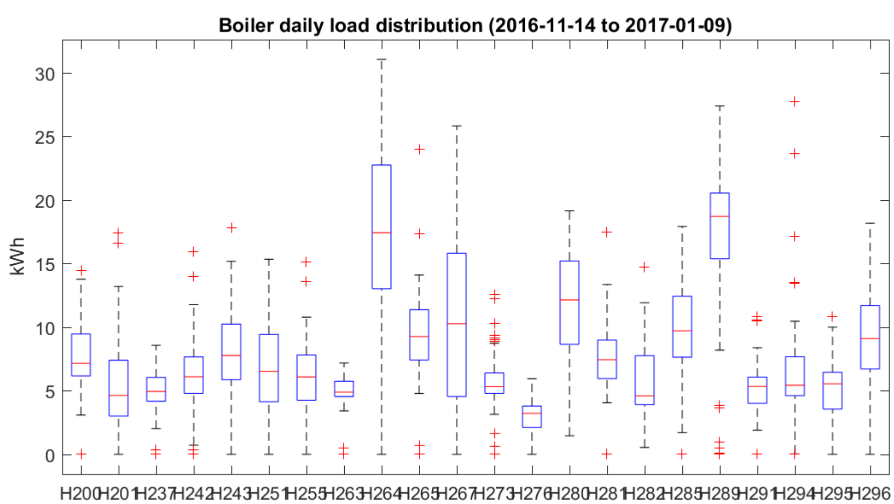

Figure 6-4: Boxplot of daily load for each household from 14 Nov 2016 to 8 Jan 2017 (Data source: SEMIAH pilot).

6.2.2 Market Prices

In this section, we will give an overview of the prices used in the optimisation. Four different market prices are relevant for our model described in the previous section: day-ahead prices, intraday prices, reserve option market (RKOM) prices and regulating energy prices. Out of the five price areas in Norway, Engene is located in the price area Kristiansand or NO2. Hence, we will focus on the price data for NO2 for the whole analysis. The five price regions usually have the same prices as long as capacity constraints are not binding. If capacity constraints are binding and prices differ, the gaps are usually not large.

The day-ahead prices for NO2 over the last four years are shown in the upper graph of Figure 6-5. The figure shows prices from 2013 to 2016. The time series has a mean of 232.1 NOK/MWh with a standard deviation of 69.9 NOW/MWh. It never drops below 4.9 NOK/MWh (27 Oct 2014) and reaches its maximum at 912.2 NOK/MWh (20 Jan 2016). Consistent with the general Norwegian load profile, prices are generally higher in the winter than in the summer due to higher demand during the cold months. From 2013 to 2015 prices were falling but they recovered in 2016 again.

The temporary high in 2016 is explained by a very cold winter in the Nordics compared to the rest of Europe and the declining hydro and wind power generation. NordPool was forced to import electricity from the neighbouring southern countries. Usually Norway has a positive power balance. Another factor that helped stabilise the price in 2016 was the new interconnections between Lithuania and Poland and between Lithuania and Sweden. Export to those countries increased so that overall demand in the Nordics was higher and prices rose [105].

In the lower graph of Figure 6-5, we see the hourly returns of the NO2 prices for the years 2013 to 2016.[27] It is noteworthy that prices during the winter of 2013 and 2014 fluctuated very little. This contrasts with the years 2015 and 2016 when price volatility was relatively high. By only looking at this data, there is no evidence that the volatility increase is permanent or only temporary in nature.

[27] The returns are derived as the difference in price between two hours at t and t+1 divided by the price at t.

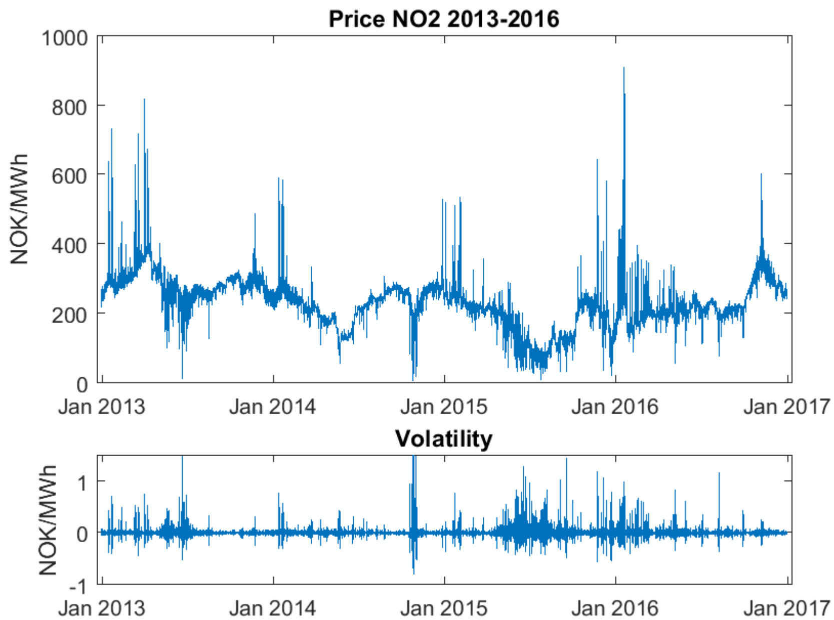

Figure 6-5: Elspot prices: Upper plot – NordPool Elspot NO2 area hourly day-ahead prices from 1 Jan 2013 to 8 Jan 2017. Lower plot – Hourly returns (volatility) of NordPool Elspot NO2 area hourly day-ahead prices from 1 Jan 2013 to 8 Jan 2017 (Data source: NordPool).

Figure 6-6 presents further analysis of the spot prices with a Price Duration Curve (PDC). From 2013 to 2015 the curve shifts down every year. Only in 2016 the curve shifted back to the level of 2014. This shows again the general decreasing price level since 2013 with the recent increase in prices. Over the whole four years, the PDC has become steeper each year. Especially in 2016, the highest upper part of the PDC has become steep. This indicates that the variation in price has become higher over the whole year and therefore volatility may have increased too. Higher variation in price and volatility would increase the value of flexibility since larger price differences increase the possibilities for profiting from price optimisation. In a further assessment of DR within the SEMIAH project, price volatility has been identified clearly as the most important factor for price optimisation, more so than the actual price level or the number of aggregated households [106].

However, the historic description of the spot prices is only of limited help. What matters are price paths in the future. Expectations of the future power markets are driven by significant changes and a high level of uncertainty. This makes adequate price forecasting in the medium and long run difficult. In Norway, things might be slightly easier since the supply side is rather stable. Not enough precipitation and long periods of cold are mainly driving large price fluctuations on the supply side. The demand side on the other hand is set to change. Demand is growing and more interconnections to neighbouring countries are being established. Even though the interconnectors could in principle have a stabilising effect on a country's electricity price, this seems unlikely for Norway. The easily controllable hydro power has provided a stable environment in Norway during the last decades. Unless the country would satisfy its electricity demand by nuclear or coal fired power plants, an even more stable environment from the supply side seems unrealistic. Consequently, all the disruptive changes on the demand side will increase price volatility at least in the medium term. Norway is often referred as Europe's green battery and thus could absorb some of Europe's supply and demand fluctuations.

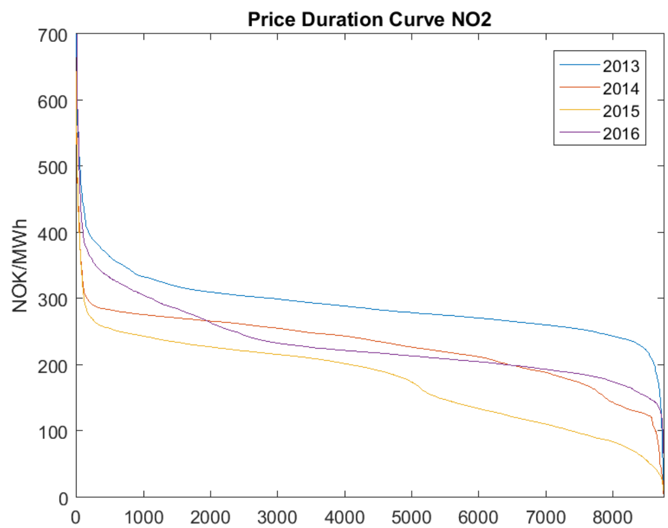

Figure 6-6: Duration curve of NordPool Elspot NO2 area hourly day-ahead prices from 1 Jan 2013 to 8 Jan 2017 (Data source: NordPool).

Unfortunately, the intraday market for NO2 is not very liquid and only one hour bids are typically submitted. For many hours during the day there is no quoted price or it is not too different to the day-ahead price [107]. Consequently, we are not considering the intraday market in our optimisation.

As mentioned, the period for the optimisation will be November 14, 2016 – January 8, 2017. As a next step, we will now look at the spot prices on NordPool, the RKOM prices and regulating energy prices. In Figure 6-7, the day-ahead prices as well as the prices of high quality RKOM (RKOM-H), low quality RKOM (RKOM-B) and the up-regulating energy prices are pictured. The mean of the NO2 spot price during this specific period is 290.3 NOK/MWh with a standard deviation of 26.8 NOK/MWh. The initially high prices of around 340 NOK/MWh fell until December 12, 2016 when it stabilised around 280 NOK/MWh. The price reaches its maximum at 370.2

NOK/MWh (21 Nov 2016, 09:00) and the minimum is at 236 NOK/MWh (22 Dec 2016, 02:00). In addition, there is one peak at 351.1 NOK/MWh (5 Jan 2017, 08:00) which coincides with the peak in the load of the Engene Transformer and the pilot community on January 5, 2017 (hour of the day differs however).

The prices for high and low quality RKOM are reflected as weekly power bands during the day hours (05:00-00:00). Their prices are identical for all weeks except the last one, when RKOM-H is priced higher. The RKOM prices for the night hours are not shown because they are equal to zero during the whole period considered. Generally, all the RKOM prices are low and stay around 10 NOK/MW/h during the whole period. They reach zero before they rise to their maximum of 30 NOK/MW/h during the last week. Since prices are per hour, one would receive 1330 NOK for providing one MW of capacity for one week during daytime at the price of 10 NOK/MW/h.[28] In 2016, the highest price was 130 NOK/MW/h. During the summer month prices are usually zero because RKOM is generally only required during winter (October until April).

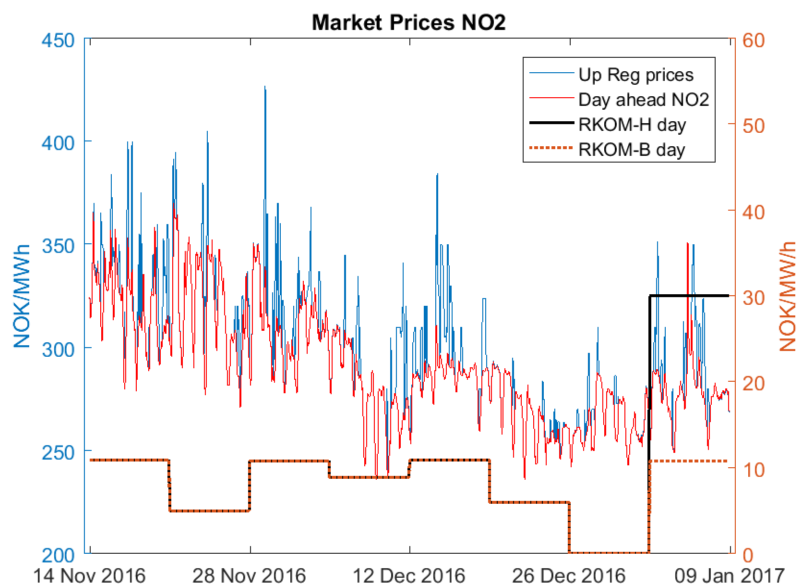

Figure 6-7: NordPool Elspot NO2 area hourly day-ahead prices, NO2 Up-regulation prices, high and low quality reserve option market prices from 14 Nov 2016 to 8 Jan 2017 (Data source: NordPool).

Overall the prices for tertiary control reserve capacity (RKOM) seem low, which does not come as a complete surprise. Norway's hydro power production is very flexible and can be controlled easily compared to other country's power generation, with a higher share of wind or solar power, e.g. Germany [108]. To determine the true revenue from

[28] 10 NOK/MW/h * 19 h * 7 d = 1330 NOK

offering tertiary control reserves, one also must consider the activation reimbursement for the energy delivered, which is reflected in the Up-regulation price. This price is paid per MWh and always at least equals the spot price of the relevant hour. The Up-regulation price has a mean of 298.6 NOK/MWh with a standard deviation of 31.8 NOK/MWh. The maximum lies at 427.9 NOK/MWh which is clearly above the normal NO2 day-ahead price level. The minimum is at 236 NOK/MWh, the same as for the day-ahead price.

6.3 Method

Referring to the DSO and Aggregator models previously presented in Figure 6-1 and Figure 6-2 respectively, we start by modelling the household flexibility, which in our case is the boiler load.

Referenced in section 3.2, Ottesen and Tomasgard in [47] develop a stochastic model for scheduling load of a flexible building based on future price and energy demand expectations. They usefully define load types into different categories, where boilers can be defined as 'Shiftable Volume Loads' in which the total volume of load must be met over a certain time-period, e.g. 24 hours, but the profile of this load can be changed. Figure 6-8 gives a visual demonstration of this load type, used in Ottesen and Tomasgard [47]. The diagram on the left shows the load before optimisation, with the load of a certain profile occurring in time periods 2 to 5, totalling 9 units of energy (each square block equals 1 unit). Here this load is named 'Forecast' but in our case, it would have been already observed. The diagram on the right shows how the load can be shifted to time-periods 1, 7 and 8, with a different profile, but the total load for the whole period 1 to 8 is still the same as before – 9 units.

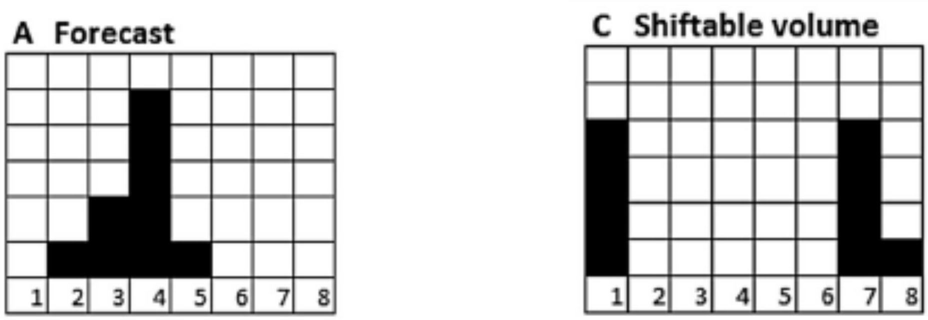

Figure 6-8: Demonstration of shiftable volume load, from [47].

Our model will respect the above load type, however instead of scheduling load for future time-periods, our approach is a deterministic ex-post optimisation in which we use already observed demand and prices. With this data, we optimise the load path to reduce costs for the DSO – 'DSO Model' – or maximise profit for the aggregator – 'Aggregator Model'. The cost reduction in the DSO model will be in the form of long-term investment costs, achieved by an optimisation that reduces the highest peaks in total load. The profit will be maximised for the aggregator in the aggregator model by optimising the load based on observed market prices in the day-ahead and ancillary services markets.

In a real-world setting, the aggregator would of course be optimising load based on forecasted demand and market prices. The accuracy of the forecasting would therefore represent a significant extra layer to the financial success of a DR system for an aggregator. In addition, the aggregator will need to consider the impact that making consumers aware of daily price fluctuations ahead of time will have on the realised demand and market prices. Future aggregators will need to ensure they control for these factors.

Since our prices and demand are already fixed, the focus of our optimisation is therefore to accurately model a boiler load path that would give the most flexibility, whilst maintaining an acceptable level of comfort for the user – i.e. sufficient hot water when they demand it. In co-operation with one of our thesis partners Misurio AG, we developed two distinct methods in which to allow the load to be altered and optimised within a path that should be acceptable for the pilot households. The sieve method was devised by Misurio AG and approved by the authors. The intellectual property of the sieve method is therefore owned by Misurio AG. The 4-hour block method was a suggestion of the authors', largely for comparison/sensitivity analysis against the sieve method. Both methods are applied to the DSO model and aggregator model separately, to in effect run two methods on two optimisation models.

6.3.1 Sieve Method

The term 'sieve' references the cooking utensil used to filter larger particles from smaller ones, perhaps when make a sauce of even consistency. The sieve method filters the boiler load through various constrained time intervals to deliver a path consistent with the historic use of each household boiler and therefore ensuring a level of user comfort. We consider the boiler consumption for each individual household and break up each day into time intervals of 1, 2, 4 and 8 hours. We also take those same intervals and shift them forwards by half their duration, creating an extra set of intervals. For example, the 16:00-17:00 period of 1 hour, is shifted to give a new, additional time interval 16:30-17:30. This therefore also creates intervals that overlap each day between 23:30-00:30.

We then consider all days in the 8-week testing period and find the minimum and maximum values of boiler consumption in each of the above defined intervals, for each household. For example, we take one household and look at the lowest and highest value for boiler consumption across all days during the interval 10:00-12:00. If the minimum value is 0.5 kWh (i.e. a 2 kW boiler being on for a total of 15 minutes during the 2-hour period), over the whole 8-week period, we can say it is unlikely that this household will ever demand less than 0.5 kWh during this interval, and therefore we should never allow consumption in this interval to drop below 0.5 kWh. We also apply the same logic to the shifted intervals, to add further constraints to the load path. One final constraint is that on each day the total boiler consumption post-optimisation is the same as pre-optimisation, i.e. the load profile can change through the day, within the bounds described above, but the total boiler consumption for the whole day must remain the same. This is the fundamental constraint which makes this a 'Shiftable Volume Load', as defined above from Ottesen and Tomasgard [47].

Figure 6-9 gives a visual demonstration of how these interval minimum and maximum values are defined. The diagram shows all boiler consumption values during non-shifted 2-hour time intervals for household H200. Looking at the first period 00:00-02:00 we see the minimum value across the 8-week period was 0 kWh and the maximum was 1 kWh. This means in our post-optimisation path, there must never be a 00:00-02:00 period on any day for household H200 where the boiler consumption exceeds the bounds of 0-1 kWh. Similarly, for 06:00-08:00 there must never be a day where the bounds of 0-3.1 kWh are exceeded. Figure 6-10 shows the same household H200 for the shifted 2-hour time intervals. Here you see the first interval running from 01:00-03:00 and the final interval running from 23:00-01:00. The above process is repeated for all the time intervals defined previously.

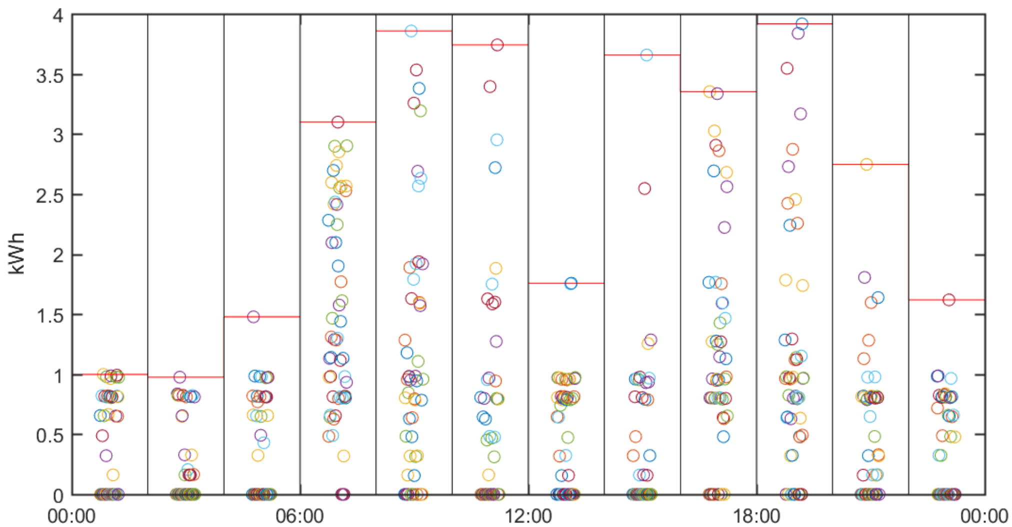

Figure 6-9: Maximum and minimum values in the 2 hour intervals for Household 200 from 14 Nov 2016 to 8 Jan 2017 (Data source: SEMIAH pilot).

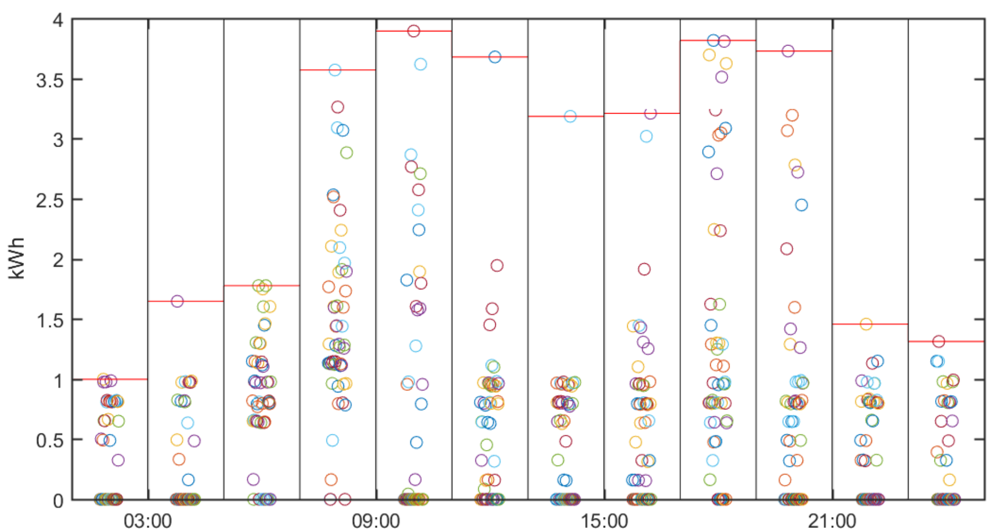

Figure 6-10: Maximum and minimum values in the 2 hour shifted intervals for Household 200 from 14 Nov 2016 to 8 Jan 2017 (Data source: SEMIAH pilot).

Once the minimum and maximum values are defined for each interval, an allowable boiler consumption path can be mapped out for every day, for each household. The allowable range therefore represents the boiler consumption path that the optimisation operates in, for every day during the 8-week testing period.

To illustrate, Figure 6-11 maps out what this would look like for all the shifted and non-shifted intervals for household H200. The white areas represent the range of the minimum and maximum values recorded for the boiler consumption for each interval for H200. The blue area represents values that have never been recorded during these intervals. The third plot down is the 2 hour non-shifted intervals. Comparing this third plot with Figure 6-9, you can see the how the height of each white area matches with the height of the red horizontal lines in Figure 6-9. The same can be said when comparing the fourth plot down, which is the 2 hour shifted intervals, with Figure 6-10.

Therefore, for every day in H200, the boiler load profile must find its way through the white areas in Figure 6-11, whilst also maintaining the same total boiler consumption for the 24-hour period.

This new optimised path is plotted in 15-minute blocks. Each of these blocks is marked as 'on' or 'off'. When 'on', the boiler consumption in kWh for that block is equal to the B_i, where B_i is one-quarter (i.e. 15/60) of the validated power rating of each household i boiler – normally very close to 2 kW. When 'off' the boiler consumption is 0.

In Figure 6-12, the red line shows how this consumption path was plotted in one of our optimisation results, on December 20, 2016 for household H200. The red line therefore represents the load profile of the boiler throughout the day during each interval. Note, as with Figure 6-11, each plot has a different scale on the y-axis, so the total kW at each stage is not easily comparable between each plot. However, by summing each interval in pairs, for example comparing the sum of the two 1 hour intervals between 00:00-02:00 with the one 2 hour interval, you can see how the loads add up for each interval. Also to note is that no red line is shown in the first and last intervals of the shifted intervals in plots 2, 4, 6 and 8. This is because these intervals cross the previous and following day respectively, i.e. the interval is shared between the days. For example, the first interval in the second plot of 00:00-00:30 is only half of this interval, the other half is 23:30-00:00 from the previous day. The query to generate this load path diagram could only process one day at a time and therefore could not show the red line in these intervals.

In analysing all maximum and minimum values as above, we extract a range for boiler consumption during different times of the day and effectively achieve a range for expected boiler demand, i.e. a load profile, for each household, for the whole testing period. The model will therefore deliver a new optimised path for each household that is within user's tolerances to ensure user comfort levels, whilst allowing sufficient flexibility.

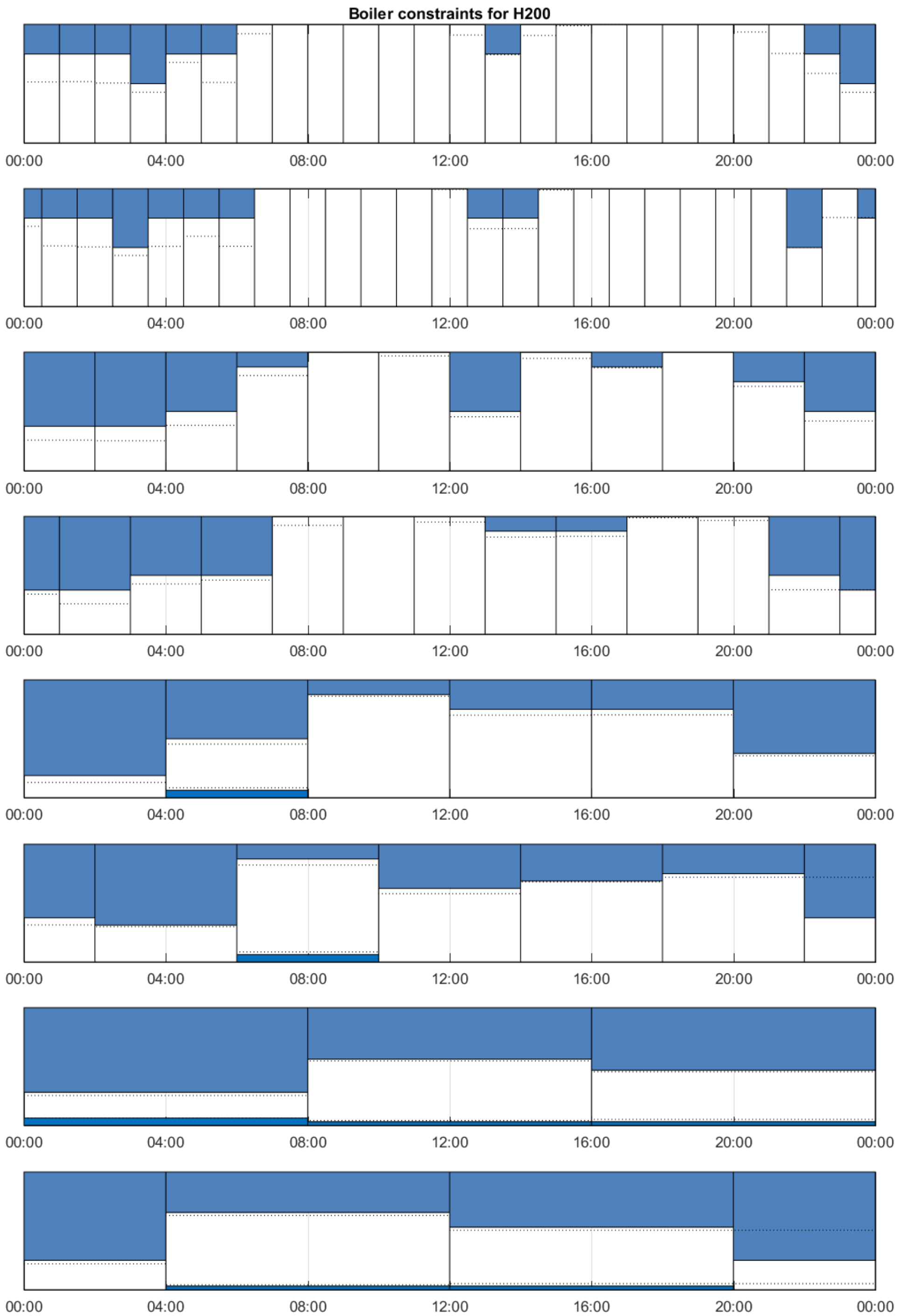

Figure 6-11: Allowable boiler consumption values for all shifted and non-shifted intervals for household 200. The horizontal dotted lines are where an upper or lower bound recorded value does not precisely match with the operation of the binary model where the boiler can only be completely on or off in 15-minutes blocks at the same power rating (B_i as defined below). For example, the upper bound may be a value of 2.8 kWh where a 2 kW boiler was on for 1 hour 24 minutes during the interval, however, with a power rating of 2 kW, the binary model can only work in 15 minute blocks of 0.5 kWh, therefore the nearest value to 2.8 kWh is 3.0 kWh and therefore this value is used. (Data source: SEMIAH pilot).

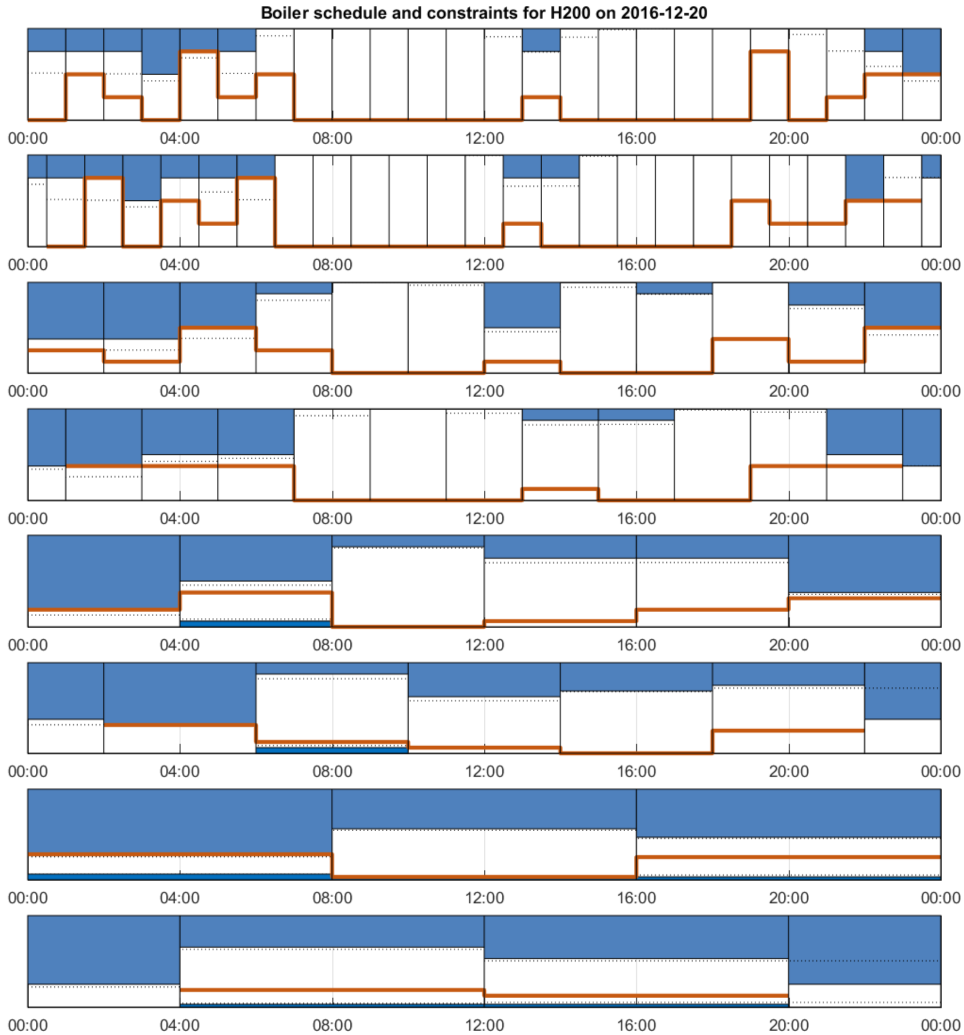

Figure 6-12: Optimised boiler consumption path for all shifted and non-shifted intervals for household 200 on December 20, 2016.

To add further constraint to the model, we decided to also include optimisations where we do not use the full extent of the minimum and maximum values. We run one optimisation excluding the lowest and highest 10% of observations and one excluding the lowest and highest 20% of observations. We therefore will run three optimisations using the sieve method – one with the full minimum and maximum range, one between the 10% and 90% quantiles and one between the 20% and 80% quantiles. To illustrate, Figure 6-13 and Figure 6-14 show how the same 2-hour bounds for household H200 in Figure 6-9 and Figure 6-10 would be set for the 10-90% optimisation.

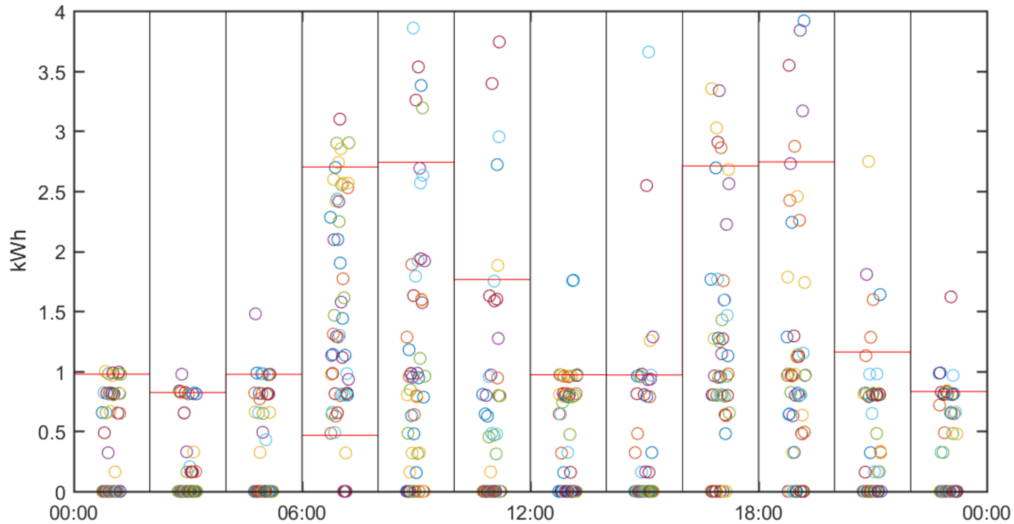

Figure 6-13: Maximum and minimum values in the 2 hour intervals for Household 200 from 14 Nov 2016 to 8 Jan 2017 with 10% and 90% barriers (Data source: SEMIAH pilot).

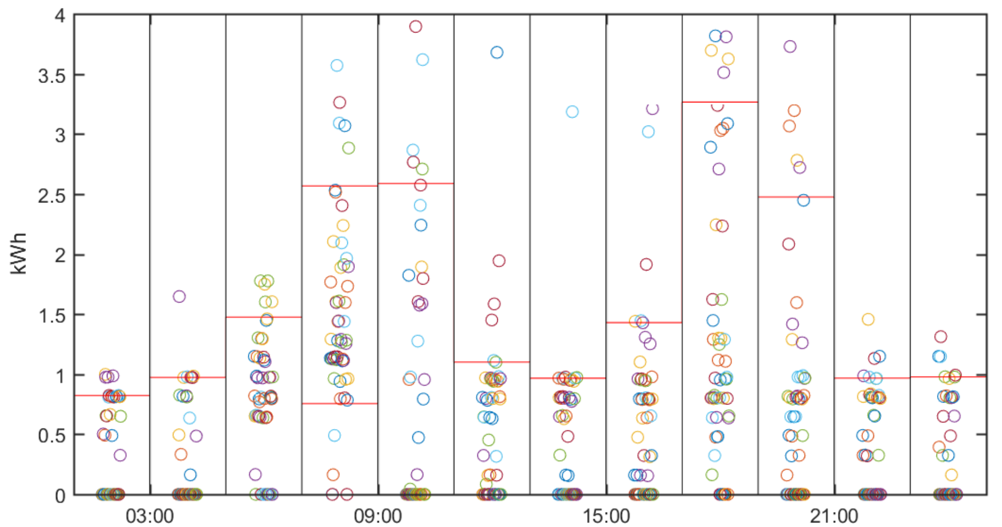

Figure 6-14: Maximum and minimum values in the 2 hour shifted intervals for Household 200 from 14 Nov 2016 to 8 Jan 2017 with 10% and 90% barriers (Data source: SEMIAH pilot).

We include these two extra optimisations as they can effectively work as sensitivity analysis to our model. In comparing the results of the full range versus the 10-90% and 20-80% models, we can see how much these added constraints restrict the flexibility of the system. Tightening the ranges does have some side effects however. In removing the lowest 10% or 20% of the observations, the load profile could be raised at certain times of the day. This will restrict flexibility but should ensure better user comfort as the boiler must be on for longer during this period, reducing the possibility of hot water running out. Removing the top 10% or 20% however, could reduce the amount the boiler must be on and therefore will restrict flexibility and potentially also user comfort by increasing the possibility of no hot water during higher demand periods. See for example in Figure 6-13, for the period 06:00-08:00, when removing the highest 10% of observations, the red line is lowered from around 3.1 kWh to 2.6kWh, therefore lowering the allowable range of values for that time interval. In addition, removing the top 10% or 20% will force the optimised load path for each household to be lower than pre-optimisation – as these top 10% or 20% values are no longer allowed to exist. When the households are aggregated, this could smoothen the load curve for the pilot community and effectively force peak shaving before the optimisation has begun. Nonetheless, as mentioned above, we include these two extra optimisations as a form of sensitivity analysis, with the above weaknesses identified.

This method, along with the 4-hour block method presented in the following section, allows us the attain an optimised range for boiler consumption, without the need for the boiler water temperature as an input. This therefore delivers a simpler model with less data requirements. Not only was the quality of the boiler temperature data poor for our pilot households but we were informed by the technology expert partners in the SEMIAH project that the accuracy of sensors meant that the boiler temperatures were not sufficiently reliable for use in detailed modelling. In addition, studies by other partners within the project showed significant flexibility in using the boiler whilst still maintaining sufficient water supply[29]. In light of the above, and the significant additional challenges in modelling the behaviour of each individual boiler, we decided to proceed with a model that did not use the boiler temperature. Particularly considering the relatively high resting temperatures of the boilers, we believe this model does deliver a decent assurance of user comforts. For a more secure guarantee that user comforts are not breached, a 'real-world' DR system must include constraints that do not allow boiler temperature to fall below set limits.

[29] As part of the SEMIAH project, the power source was cut for 18 boilers in the Swiss pilot for 1, 2, 3 or 4 hour periods at different times of the day on January 23 – January 26, 2017. Power cuts of 3 hours induced temperature decreases of only between 0.59°C and 1.71°C. Only 20-60 minutes of subsequent heating was required to compensate for this heat loss [102].

6.3.2 4-Hour Block Method

The 4-hour block method is far simpler than the above described sieve model and simply states that the post-optimisation boiler consumption for each independent 4-hour block of time should be equal to the pre-optimisation total. For example, if between 04:00-08:00 on December 1, 2017 the total boiler consumption of a particular household was 3 kWh, then the post-optimisation value for this distinct period must be the same. Therefore, the path with which the load takes can vary in any direction it likes within the 4-hour period, but the total consumption must remain the same. The new optimised path is again allocated in 15-minute blocks.

As compared with the above sieve method, the 4-hour block model therefore has more direct control over the consumption in the specific historic time-period and perhaps more effectively ensures user comfort, however naturally may yield less flexibility due to forcing exact pre-optimisation consumption on a 4-hour basis rather than a 24-hour basis. In addition, as the blocks are never shifted, there may be a possibility for squeezing consumption at opposite ends of the blocks, giving large areas of zero consumption. For example, consider the three blocks 04:00-08:00, 08:00-12:00 and 12:00-16:00. Say the consumption in each block is 3 kWh, 0 kWh and 1.5 kWh respectively. Pre-optimisation, the 0 value in the middle period could have been possible due to, for example, all 3 kWh in the first period being used from 06:30-08:00 and all 1.5 kWh in the third period being used 12:00-12:45. In a new optimised path, the 4 hour block model just states that the total consumption over each 4 hour block must be the same, therefore, if optimal, the 3 kWh in the first period could be delivered 0:00-01:30 and the 1.5 kWh in the third period could be delivered 15:15-16:00. This would create a gap of 13 hours and 45 minutes where the boiler is never turned on. One would expect in this case that the user is quite likely to experience 'discomfort' in that there may not be sufficient hot water available to meet demand during the 13 hour 45 minute off period. The above is of course an extreme example, however it illustrates a major potential shortcoming of this model. We still include this model in our analysis, however, for comparison/sensitivity analysis against the sieve method.

Both the sieve method and 4 hour block method create a load path in which the optimisation can run. Each optimisation will be run based on the following objective functions of the DSO model and aggregator model.

6.3.3 Aggregator Model

$$min \sum_{i \in I} \sum_{t \in T} x_{i,t} . B_i . E_t \tag{1}$$

$$x_{i,t} \in \{0,1\} \qquad \forall i \in I, \forall t \in T \tag{2}$$

Where binary variable $x_{i,t}$ represents whether the boiler is on ($x_{i,t} = 1$) or off ($x_{i,t} = 0$) for each i household for time period t, parameter B_i is the boiler power rating in each household i and parameter E_t is the Elspot day-ahead price for time period t. I is the set of i households. t represents each individual 15-minute block where the boiler has to be either on or off for the whole period. T is the set of t time periods. The objective function is to minimise the total costs to the aggregator of supplying the electricity to the households by minimising the cost of purchasing $\sum_{i \in I} \sum_{t \in T} x_{i.t} . B_i$ units of power at a price of E_t.

T is the set of all t. The following partitions of T are used in subsequent constraints. A partition is a series of non-empty subsets that sum together to form the complete set (T), where each element (t) of the set (T) is included in one and only one of the subsets. This is the case with the following partitions that represent a series of time intervals, where each time interval is a subset of T containing a defined number 15-minute blocks t.

Partition	Description	t units per interval
T_1	Partition of 1 hour non-shifted intervals	4
T_2	Partition of 1 hour shifted intervals	4
T_3	Partition of 2 hour non-shifted intervals	8
T_4	Partition of 2 hour shifted intervals	8
T_5	Partition of 4 hour non-shifted intervals	16
T_6	Partition of 4 hour shifted intervals	16
T_7	Partition of 8 hour non-shifted intervals	32
T_8	Partition of 8 hour shifted intervals	32
T_9	Partition of 24 hour intervals	96
T_{10}	Partition of 7 day weeks	672

Table 6-1: Partitions of time periods.

Sieve Method Only

$$L_{i,s} \leq \sum_{t \in s} x_{i,t}.B_i \leq H_{i,s} \qquad \forall i \in I, \forall s \in T_n : n \leq 8 \tag{3}$$

Where parameter $L_{i,s}$ is the lowest possible value for the boiler consumption at each household i for each time interval s and $H_{i,s}$ is the highest possible value for the boiler consumption at each household i for each time interval s. The time intervals s are made up of a number t time periods and are the subsets that make up each partition T_n, as defined in Table 6-1. Each partition represents the time intervals defined for the sieve method discussed in section 6.3.1. The values for $L_{i,s}$ and $H_{i,s}$ are dependent on which type of the sieve method is used – full MinMax, 10-90% or 20-80%. This constraint ensures that the optimised value for boiler consumption $\sum_{t \in s} x_{i,t}.B_i$ does not go outside the pre-defined ranges as discussed in section 6.3.1.

$$X_{i.d} = \sum_{t \in d} x_{i,t}.B_i \qquad \forall i \in I, \forall d \in T_9 \tag{4}$$

Where parameter $X_{i.d}$ is the total boiler consumption for household i on each day d. The time intervals d are made up of 96 t time periods and are the subsets of 24 hours that make up the partition T_9 as defined in Table 6-1. This constraint ensures that for each household i, on each day d, the total optimised boiler consumption $\sum_{t \in d} x_{i,t}.B_i$ is equal to the pre-optimisation boiler consumption $X_{i.d}$.

4-Hour Block Method Only

$$X_{i.s} = \sum_{t \in s} x_{i,t}.B_i \qquad \forall i \in I, \forall s \in T_5 \tag{5}$$

Where parameter $X_{i.s}$ is the total boiler consumption for household i during each independent 4-hour block s. The time intervals s are made up of 16 t time periods and are the subsets of 4 hours that make up the partition T_5 as defined in Table 6-1. This constraint ensures that for each household i, during each independent 4-hour block s, the total optimised boiler consumption $\sum_{t \in s} x_{i,t}.B_i$ is equal to the pre-optimisation boiler consumption $X_{i.s}$.

Reserve Option Market

For the reserve option market, after an initial optimisation on the day-ahead market, we then repeat the optimisation but take out 1 kW from the consumption available for day-ahead optimisation and allocate this to the reserve option market. This optimisation continues iteratively adding one extra kW at a time until the solution is infeasible.

$$R_w = \sum_{i \in I} X_{i,w} - \sum_{i \in I} \sum_{t \in w} x_{i,t} . B_i \qquad \forall w \in T_{10} \tag{6}$$

Where parameter R_w is the total power allocated to the reserve option market during each week w, parameter $X_{i.w}$ is the total boiler consumption for household i in each week w, binary variable $x_{i,t}$ represents whether the boiler is on or off for each i household for time period t as allocated in the day-ahead optimisation, and parameter B_i is the boiler power rating in each household i. The time intervals w are made up of 672 t time periods and are the subsets of 7 day weeks that make up the partition T_{10} as defined in Table 6-1. This constraint ensures that the total power offered in the reserve option market in each week w is equal to the difference between the total boiler consumption for each week $\sum_{i \in I} X_{i,w}$ and the total boiler consumption $\sum_{i \in I} \sum_{t \in w} x_{i,t} . B_i$ offered in the day-ahead optimisation.

Aggregator Peak Shaving

As will be further explained in the results section, we carry out tests that incrementally reduce boiler load peaks for every time period across the whole 8 weeks, in order to show the potential for an aggregator to reduce the boiler load when called upon to do by a DSO or any other customer. We also calculate the marginal cost of achieving the peak shaving versus the original day-ahead price optimisation.

$$\sum_{i \in I} x_{i,t} . B_i \leq Q \qquad \forall t \in T \tag{7}$$

Where Q is the total power in kW that the aggregated boiler load for the pilot community must not exceed. For example, if $Q = 30$ then there must be no independent 15-minute block during the whole 8-week period where the aggregated boiler load is greater than 30 kW. The value of Q is reduced incrementally by 2 kW until no feasible solution is found.

6.3.4 DSO Model

For the DSO Model, we start with the aggregator model as a base for our optimisations. The reason for this is that although the DSO may not be explicitly concerned with the procurement costs of the electricity, the consumer may indeed be. This could be in the form of a variable tariff that is linked, directly or indirectly, to the day-ahead wholesale prices. Starting with the cost minimisation therefore ensures further ‘comfort’ in guaranteeing lower procurement costs as a starting point. In addition, applying cost minimisation allows us to find a price for the changing of consumption from one period to another, i.e. a marginal price for the peak shaving.

$$min \sum_{i \in I} \sum_{t \in T} x_{i,t} \,.\, B_i \,(E_t + P_t) \tag{8}$$

$$x_{i,t} \in \{0,1\} \qquad \forall i \in I, \forall t \in T \tag{9}$$

Where binary variable $x_{i,t}$ represents whether the boiler is on ($x_{i,t} = 1$) or off ($x_{i,t} = 0$) for each i household for time period t, parameter B_i is the boiler power rating in each household i, parameter E_t is the Elspot day-ahead price for time period t, and parameter P_t is the penalty applied for non-zero boiler consumption during time period t. During the periods where the DSO wishes to reduce consumption, the penalty P_t will be a sufficiently high positive value so as to heavily discourage any boiler consumption, whilst keeping procurement costs low. P_t will be zero for all other time periods. I is the set of i households and T is the set of t time periods. The objective function is to minimise the total costs of supplying the electricity to the households by minimising the cost of purchasing $\sum_{i \in I} \sum_{t \in T} x_{i,t} \,.\, B_i$ units of power at a price of E_t and to minimise the penalty incurred from non-zero boiler consumption during peak periods.

Eq. (10), Eq. (11) and Eq. (12) below are exactly the same as Eq. (3), Eq. (4) and Eq. (5) in the aggregator model.

Sieve Method Only

$$L_{i,s} \leq \sum_{t \in s} x_{i,t}.B_i \leq H_{i,s} \qquad \forall i \in I, \forall s \in T_n : n \leq 8 \tag{10}$$

$$X_{i.d} = \sum_{t \in d} x_{i,t}.B_i \qquad \forall i \in I, \forall d \in T_9 \tag{11}$$

4-Hour Block Method Only

$$X_{i.s} = \sum_{t \in s} x_{i,t}.B_i \qquad \forall i \in I, \forall s \in T_5 \tag{12}$$

6.4 Results

The following section states the results of the optimisation that was applied based on the data and methodology explained above. The idea is to outline the most relevant findings and to give a more context related analysis. For the optimisation, the two market models were executed in reverse order than explained above. To find a marginal price for peak shaving, it was natural to optimise the boiler consumption against the market prices first.

6.4.1 Aggregator Price Optimisation

As a first step, we optimised boiler load against the day-ahead price of NO2 during our period November 14, 2016 – January 8, 2017. The optimisation was executed using four different models – the three sieve methods and the 4 hour block method. Putting the optimisation into the market context, one can imagine the aggregator trying to buy electricity as cheap as possible for his customer. Simultaneously, he must guarantee the comfort settings of the households are not violated. In the sieve and the 4 hour approach, this is done implicitly.

In Table 6-2, we can see that in the actual aggregated household data the overall hourly peak was 96 kW, while the maximum of aggregated boiler power was 26 kW. The share of boiler consumption in the total consumption across the whole period, is

13.3%. This is since the boiler heats relatively often to keep the water temperature on the desired level but only for a short amount of time. Total boiler procurement costs are also about 13.3%. One notes that based on the method applied, total consumption stays constant for all optimisations, only peak loads and procurement costs will change.

In the first optimisation, the sieve boundaries were based on the minimum and maximum for the selected intervals. Without putting any further constraints, we see clearly that both total peak load and boiler peak load increases, while procurement costs decrease by approximately 120 NOK. We decreased the level of flexibility by using the $10^{th}/90^{th}$ and $20^{th}/80^{th}$ percentile for the sieve boundaries. Peak load increases less than in the MinMax case but savings on procurement costs also decrease. The 4h optimisation is the strictest one and provides the least boiler flexibility. Cost savings decrease to approximately 37 NOK and peaks still increase.

	Peak load [kW]		*Consumption [MWh]*			*Procurement Cost [NOK]*		*Cost reduction [NOK]*	
	Total	Boiler	Total	Boiler	Boiler share	Total	Boiler	Boiler	
Actual Data	96.0	26.0				21081.6	2822.7	-	-
MinMax	109.2	42.2				20961.5	2702.6	120.1	4.3%
q10% - q20%	104.2	39.2	72.57	9.6	13.3%	21005.5	2746.7	76.0	2.7%
q20% - q80%	102.3	35.2				21032.3	2773.5	49.2	1.7%
4h blocks	106.8	41.3				21044.5	2785.6	37.1	1.3%

Table 6-2: Original data compared to the results of the day-ahead price optimisations with different levels of flexibility. Note: total consumption and boiler consumption is constant for all methods at 72.57 MWh and 9.6 MWh respectively.

Considering that our objective is shaving peaks, the increase of the total and boiler peak seems problematic, at least for the DSO. However, from an aggregator point of view this makes sense. If there are no appropriate price mechanisms for grid capacity in place, he would not care about high peaks. As long as he can reduce his procurement costs, he will optimise against the interests of DSOs. Nevertheless, the issue will be addressed in the following sections. It will be shown that peaks can be kept or reduced for little costs.

The savings in procurement costs are rather low for all the optimisation results. We have identified two potential reasons for that. Firstly, typical boiler consumption in Norway appears all over the day, for relative short periods to keep the water temperature within the defined temperature range. Thus, even though much of the consumption can be shifted to another point in time, only a very small fraction can profit from the price gains. Secondly, the hourly price volatility in NO2 for the investigated period is very small. Thus, the optimisation cannot profit from large price differences.

One should note that in all our optimisations the absolute changes in numbers are small and we must be careful with our conclusions drawn. The small changes in the objective function can trigger the termination condition of a Mixed Integer Program (MIP) and result in an early stop of the optimisation. Also, the duration restriction of 300 seconds can trigger the MIP termination conditions, stopping the optimisation before the best feasible solution is reached. In these first four results, however, none of these MIP conditions were triggered.[30]

Figure 6-15 shows the day-ahead prices for NO2 as well as the aggregated observed and optimised boiler data for 25 Dec 2016. The day was picked since it is Christmas Day and usually people in Norway are home. Thus, many devices and heating systems are on so that the behaviour of optimised load can be shown clearly. In the first graph, we see a clear peak in price around lunch time. In the second graph, we can see the observed boiler consumption over the whole day, which is positively correlated to the price curve. On the contrary, the optimised boiler load in graphs three to six show a negative correlation to the price curve. It is also visible that the stricter the boundaries are, the less the optimisation path can be dictated by the price. The MinMax optimisation can force the price pattern on the consumption pattern the most.

The outcome of the 4-hour optimisation is relatively uneven and does not seem very realistic, since it leaves many hours a day with zero aggregated consumption. Therefore, contrary to our expectations, the 4-hour block approach looks to perhaps provide less assurance of consumer comfort. This is due to the weakness of the model explained in detail in section 6.3.2, noting large gaps like this could occur. Despite this fact, the approach still is helpful since it serves as our least optimistic outcome.

[30] The type of optimisation used can be terminated early if certain constraints are binding. One is the duration restriction, here 300 seconds, and another is the absolute MIP gap tolerance. The absolute MIP gap tolerance is a limit on the difference between an integer objective value and the objective value of the best node remaining. When the gap between the two values in the current solution falls below the MIP gap, then the optimisation is terminated [119].

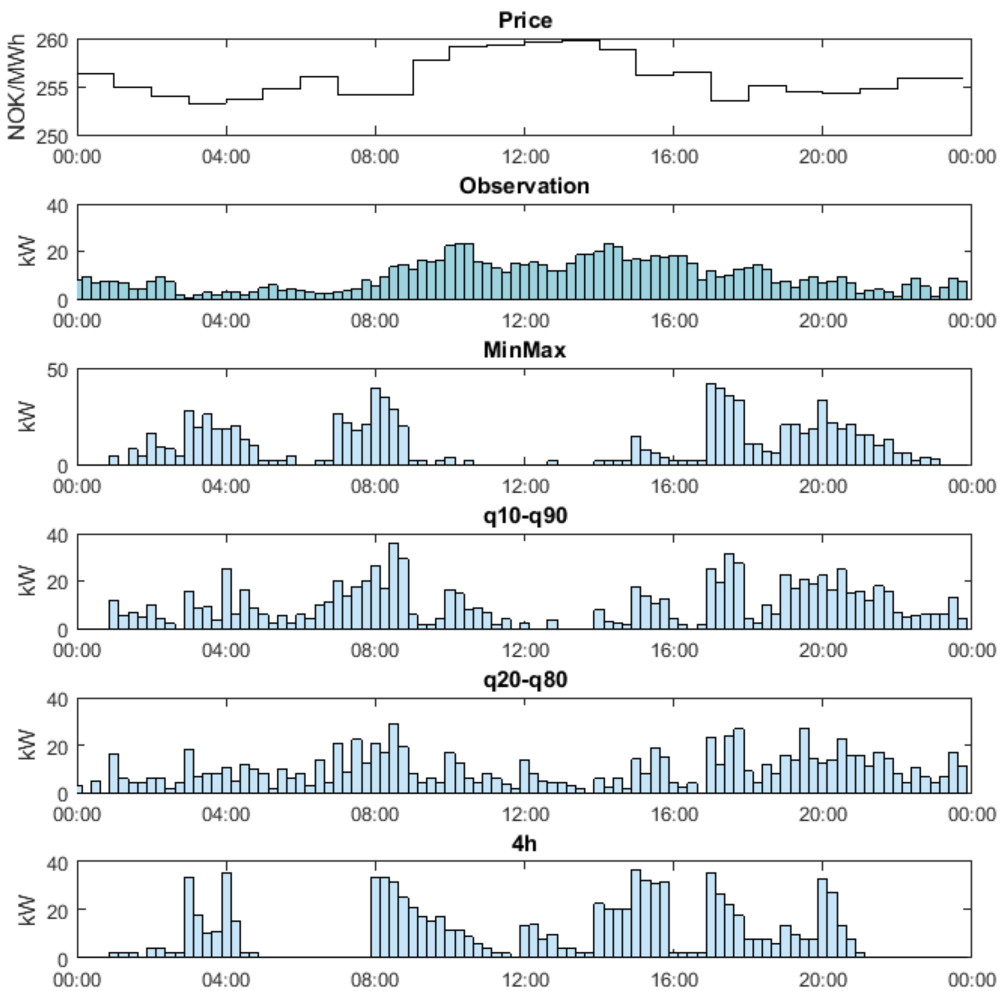

Figure 6-15: Observed optimised boiler load for all level of optimisation rigidity plotted against the price level on 25 Dec 2016 (Data source: NordPool).

6.4.2 Aggregator Peak Shaving

In a second step, the optimisation in all four types was run with an additional constraint (Eq. (7) in section 6.3.3) trying to reduce the boiler only peaks. Even though we do not shave the total overall peaks with this method, we get some interesting insights about the existing boiler flexibility. The method tells us how much boiler peaks can be reduced during hours with high boiler consumption. In addition, we see how much the optimal procurement costs are affected, giving us a marginal price.

For each type, we have run an optimisation that limited the boiler peak to a certain level using the first optimisation form above as a starting point. The optimisation was repeated by reducing the boiler peak in 2 kW steps until the solution became unfeasible.

The stepwise approach allows us to see the different increments in costs for shaving the peaks as visible in Figure 6-16. For the MinMax and the 10th/90th percentile optimisations the solution became unfeasible below 12 kW boiler peak over the whole time period considered. For the 20th/80th percentile optimisation the final stop was at a 14 kW boiler peak and for the 4 hour optimisation at 18 kW as visible in Table 6-3.

	Peak load initially [kW]		*Peak load shaved [kW]*		*Boiler proc. costs [NOK]*		
	Total	Boiler	Total	Boiler	Initially	Shaved	Diff
MinMax	109.2	42.2	95.0	12.0	2702.6	2740.6	38.0
q10% - q90%	104.2	39.2	94.7	12.0	2746.7	2759.8	13.1
q20% - q80%	102.3	35.2	96.6	14.0	2773.5	2776.3	2.8
4h blocks	106.8	41.3	99.9	18.0	2785.6	2792.9	7.3

Table 6-3: Applying incremental boiler peak shaving optimisation to the four different optimisation types. Comparing the initial boiler energy procurement costs and the ones after the optimisation gives us an estimator for a marginal price for such a service.

The price for the reduction varies considerably depending on the method used. One might assume that the stricter the boundaries of the optimisation are, the more expensive it becomes to reduce it. However, that logic does not apply here. The looser the boundaries the more flexibility was exploited against the price. The tighter the constraints, the less the price potential is used and the smaller the effects of the peak shaving have on the procurement costs. While the costs of reducing the boiler peak for the MinMax optimisation from 42.2 kW to 12 kW were 38 NOK, for the 10th/90th percentile it only costs 13.1 NOK to reduce the boiler peak the same amount. The difference in the boiler procurement costs before and after the optimisation can be interpreted as the marginal price for shaving the peaks. In other terms, this will reflect the costs of flexibility. Nonetheless, the total procurement costs for the MinMax optimisation was still the lowest even after boiler peak shaving.

Figure 6-16 illustrates the different marginal prices of shaving the peaks in 2 kW increments for all four optimisation types. Importantly, the initial boiler peak level of 26 kW (from the observed data) can be maintained in all four optimisations at almost no costs. Even reducing the peaks to a minimum does not lead to a high marginal peak shaving price.

As warned in the previous section, we must be careful when interpreting the marginal prices. They are very small and certain boiler peak shaving optimisations do reach the duration constraint of 300 seconds. The MIP gaps increase too. Both of which indicate that not necessarily the best solution possible has been found and inconsistency is possible.[31]

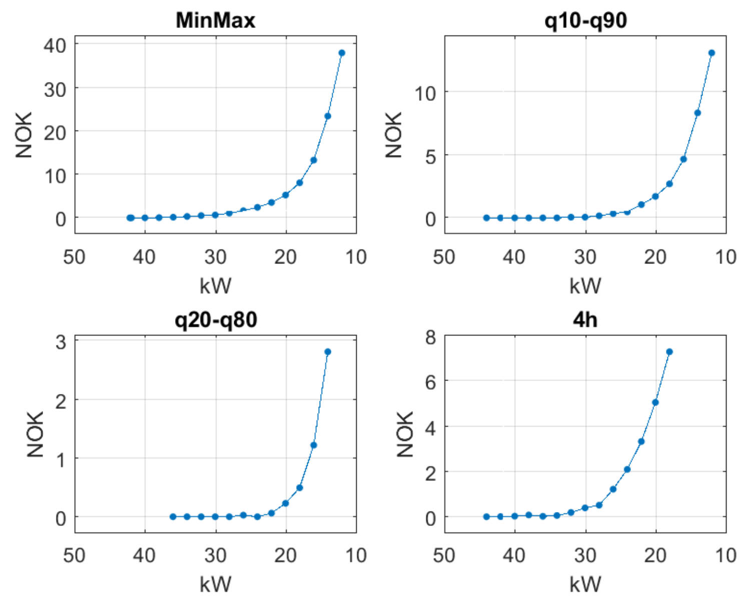

Figure 6-16: Marginal prices for shaving the boiler peaks over the whole period for each optimisation type.

The boiler peak shaving optimisation above only reduces all boiler peaks across the whole period. The next target is to reduce the highest peaks of overall consumption to a minimum. For all four types of optimisation the lowest feasible optimisation was a peak reduction to 88 kW. This equals a reduction of just over 8% compared to the observed overall peak of 96 kW. Encouragingly, the marginal price for all four optimisations is almost equal to zero see Table 6-4.

	Peak load initially [kW]		*Peak load shaved [kW]*		*Boiler proc. costs [NOK]*		
	Total	Boiler	Total	Boiler	Initially	Shaved	Diff
MinMax	109.2	42.2	88.0	42.1	2702.6	2702.9	0.3
q10% - q20%	104.2	39.2	87.9	38.2	2745.5	2746.8	1.2
q20% - q80%	102.3	35.2	88.0	33.4	2771.9	2773.5	1.6
4h blocks	106.8	41.3	88.0	44.1	2782.0	2786.0	4.0

Table 6-4: Applying incremental total overall peak shaving optimisation to the four different optimisation types. Comparing the initial boiler energy procurement costs and the ones after the optimisation gives us an estimator for a marginal price for such a service.

[31] See Appendix A for more details on the optimisation results.

Even though the results from the optimisation did not show major cost reductions, the peak shaving cost reduction looks promising. The almost free reduction of the overall peak by 8% shows high potential of DR. The aggregator can, while still optimising against the price, offer the DSO lucrative options to reduce peaks and keep them below a certain threshold. Since the marginal price in that situation is almost zero, the question remains what would be an appropriate price for such a service. The value of flexibility and its price will be discussed further in chapter 7.

6.4.3 Aggregator Reserve Option Market

As the last step in the aggregator model, we investigated the potential of bidding on the reserve option market (RKOM) in NO2. As discussed in section 2.3.1, tertiary control reserves in Norway through RKOM involve only up-regulating capacity, producing additional energy or consuming less energy if required. The nature of boiler behaviour as a consumption unit makes it difficult to provide a power capacity band for one week. While it is relatively easy to turn them on, it is much more difficult to guarantee a long period of turning them off. Scaling and aggregation effects can help to improve the situation. When looking at several thousand households, the chances are higher that there will always be several boilers on, as compared with only 22 houses.

For our optimisation, we considered weekly day time (05:00-00:00), high-quality RKOM products (RKOM-H). Offering at night time is not very interesting at all since prices are almost always zero. The decision to only bid high-quality RKOM was due to a higher pay off while the mathematical complexity of the problem was much lower. In addition, the higher likeliness of being accepted when submitting a high-quality bid versus a low-quality one.

The optimisation was carried out repeatedly for different sizes of RKOM power bands. The starting point was at 1 kW, i.e. 1 kW of turn down power which is available every day between 05:00-00:00. The power bands were increased by 1 kW steps until the solution was infeasible. As an outcome, we received new boiler procurement costs. The difference between the initial boiler procurement costs and the result from each incremental RKOM optimisation gave us a marginal price. The marginal price can then be seen as the bidding price, which would be submitted at Statnett's RKOM. The procedure was only applied for the sieve model, since the 4-hour approach forces the consumption over four hours to be equal to the observed one, therefore a participation at RKOM is not possible.

Figure 6-17 shows the results from the RKOM optimisation. While for the MinMax approach 5 kW for one week at most can be submitted, the maximum for the other two lies at 3 kW. The stricter the constraints, the smaller the power bands that are available. This does not come as a surprise. Stricter constraints mean less flexibility, which again make it difficult to offer a guaranteed power band of a certain capacity during the whole week. For week eight there is no bid feasible due to a lack of household data for approximately one day during that week.

Except one outlier in the MinMax optimisation, the marginal prices are relatively similar for all optimisation types. This result gives us some confidence that the results are somehow robust. Nevertheless, some caution is appropriate since many of those optimisations reach the 300 second duration limit, with a relatively large MIP gap. The same phenomena we have seen when shaving the boiler and overall peaks appears again here. The more flexible the method used to optimise the day-ahead prices, the higher the cost can be for submitting a RKOM bid. For example, the marginal prices for MinMax are often higher than for the $10^{th}/90^{th}$ percentile or the $20^{th}/80^{th}$ percentile optimisation, as can be seen in Figure 6-17.

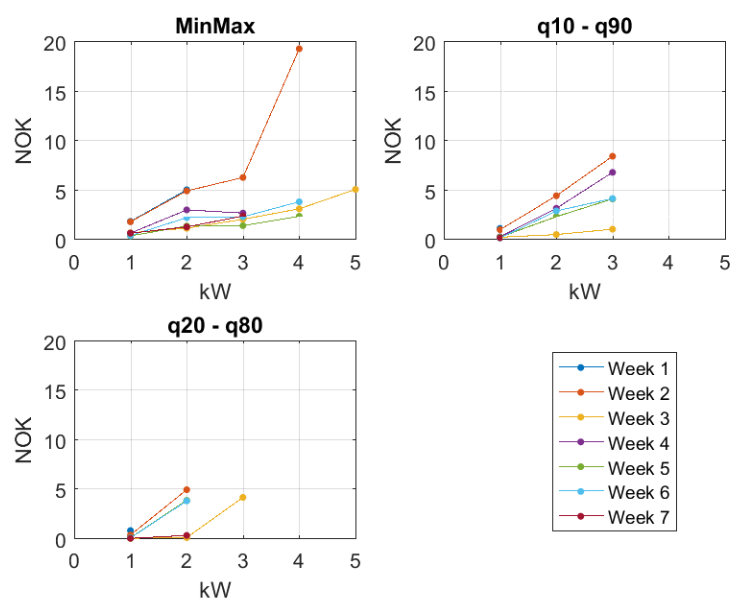

Figure 6-17: Marginal prices for different lot sizes of high-quality RKOM bids for one week.

Further, we would like to compare the different marginal prices with the actual RKOM-H market prices. That allows us to compare against the bids that were submitted under real conditions. First, we calculated how much the RKOM-H option price would have paid off in one week per kW power band provided. Where this revenue is negative, i.e. the marginal price is higher than the RKOM-H option price, it is declared that the aggregator would not participate. The highest amount of reserve capacity that is profitable is selected as the submitted bid, which we assume is accepted as the bid would have been at the price level that was accepted. With these accepted bids for capacity, we then add the income for the known up-regulation energy that was called by Statnett each week. We assume the marginal costs of providing the demand reduction are lower than those of a generator having to increase his production. Thus, the aggregator's bids for the regulating energy would all have been accepted in all hours when up-regulating energy was activated.

This process then provides us with the number of kW submitted and accepted per week, for each optimisation method, and the additional regulating energy income when called. Figure 6-18 displays these results. In the upper plot the bars show the submitted volumes in each week for the three different optimisation models and the orange line shows the per kW revenue each week, from both the option and regulating energy income. While the MinMax approach allows us to submit the highest bids in weeks three and five, the other optimisations allowed us to bid more frequently. However, in general we can see that only 1 kW hour can be offered frequently for all the approaches. In the lower plot, the bars show the total profits. Besides week three and week five for the MinMax optimisation, the profits are negligible.

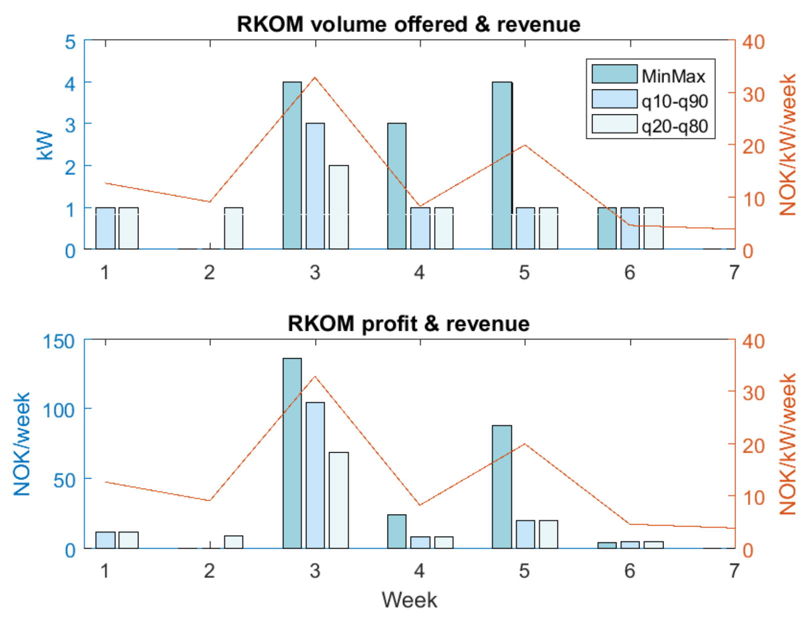

Figure 6-18: Profits and volumes from RKOM: Upper plot – volume of theoretically accepted RKOM volumes for the three different optimisation approaches and the potential revenue stream of RKOM. Lower plot – profit made from the theoretical RKOM participation and the potential revenue stream of RKOM.

During the weeks that it was profitable to participate in RKOM, the income was not high. The highest income generated was in week three when 4 kW was offered and a total profit of 150 NOK for the whole week was achieved, i.e. 37.5 NOK/kW. Most of the income was achieved by the energy which was called and not the provision of capacity. Out of the 37.5 NOK/kW, only 3.2 NOK/kW came from the capacity. The rest is from the delivery of up-regulation energy. If results such as in week three were achieved on a regular basis and for larger capacities, the participation at the RKOM could be an interesting source of income. However, the volume and the frequency that can currently be offered is simply too low.

The low volumes and thus revenues from the RKOM do not suggest an attractive business case for household boilers. A reason for that is the low boiler availability. The issue becomes smaller the more houses are combined and the more devices are integrated in the DR portfolio. The further aggregation of households should lead to a situation in which some boilers will always be available. Hence, the analysis that is done here cannot bring in enough light on the subject. Further research should repeat the approach with a larger aggregation.

Furthermore, the regulation is such that a minimum of 10 MW must be offered. Again, larger aggregation might help to mitigate the problem, as might including extra appliances such as heating systems. As already mentioned, there needs be more research on this matter to be able to make a well-founded judgement.

6.4.4 DSO Peak Shaving

Recall that in the DSO model the DSO oversees the DR system. Hence, the DSO can define its own objective functions. In our study, the DSO's interest is primarily to reduce the overall peak in Engene so his investments can be postponed or reduced. To address this issue, we started again from the day-ahead optimisation. The reason for this starting point lies in assurance of procurement costs of the households. If the optimisation would completely ignore the market price, the costs for purchasing electricity for the household or their supplier could increase significantly. Soon, more market oriented tariff models for end consumers are likely. Already now several market price based tariffs exist in Norway [109]. Consequently, keeping the purchase costs as low as possible also makes sense when the DSO controls the household flexibility.

To assess the peak shaving potential and its costs, we used several peak shaving optimisations. The different approaches are described in Table 6-5. The starting point was PS1. For PS1 the objective is to reduce the two highest peaks of the Engene transformer during the optimisation period – 18:00 29 Nov and 17:00 5 Jan – without controlling for anything else. The target in PS2 is to shave four specific peaks of aggregated load of the 22 considered households within the optimisation period, also not controlling for anything else. With PS1 and PS2 the idea was to get a feeling on how difficult it is to shave individual peaks. In case it would already be difficult to shave individual peaks during one hour, any further PS optimisation would not make sense at all.

Abbreviation	***Description***
PS1	Minimise the two highest overall peak of Engene transformer: 18:00 29 Nov and 17:00 5 Jan
PS2	Shave four highest peak hours of the aggregated 22 pilot household load curve: 17:00 14 Dec, 17:00 15 Dec, 18:00 5 Jan, 08:00 6 Jan
PS3	Avoid boiler consumption from 08:00 to 10:00 and from 17:00 to 19:00
PS3.1	PS3 but limit meter peak at 100% of measurements and boiler peak at 100%
PS3.2	PS3 but limit meter peak at 95% of measurements and boiler peak at 95%
PS3.3	PS3 but limit meter peak at 95% of measurements and boiler peak at 90%

Table 6-5: Description of the six peak shaving optimisations for the DSO model.

For PS3, we identified the peak hours of the day in Engene based on the transformer data (08:00-10:00 and 17:00-19:00) and set up the target function to minimise the boiler consumption during those hours. PS3.1 to PS3.3 are the same as PS3 but an overall peak penalty and a boiler peak penalty is added. The additionally implemented penalties in PS3.1 to PS3.3 occur if the level of the observed overall peak load and boiler peak load is exceeded. The target with PS3 was to see if consumption can be kept generally low during typical critical hours of the day. The PS3.x optimisations were added to avoid creating even higher overall peaks.

The results for all the peak shaving optimisations are shown in Table 6-6. For the peak hours in PS1, boiler consumption can be reduced to zero at no cost for all approaches except the $20^{th}/80^{th}$ percentile optimisation. In the $20^{th}/80^{th}$ percentile optimisation a penalty appears, which means that during at least one 15-minute interval of the two peak periods, it is not possible to achieve a boiler consumption of zero. During all the other time steps, it is possible to shave the peaks to zero. The outcome for PS2 is similar to PS1. In all scenarios, the peaks can be shaved at no costs except in the 4-hour optimisation. A penalty appears that indicates not all the boiler consumption can be reduced entirely to zero.

MinMax	*Peak (kW)*		*Costs [NOK]*		**q10 - q90**	*Peak (kW)*		*Costs [NOK]*	
	Total	Boiler	Boiler	Penalty		Total	Boiler	Boiler	Penalty
PS1	111.3	42.2	2702.6	0.0	PS1	104.2	40.0	2746.7	0.0
PS2	111.0	42.1	2702.6	0.0	PS2	106.1	39.2	2746.7	0.0
PS3	110.8	42.0	2704.9	209.8	PS3	104.2	39.1	2749.7	1536.1
PS3.1	-	-	-	-	PS3.1	95.6	26.3	2749.9	1536.1
PS3.2	-	-	-	-	PS3.2	90.9	25.0	2750.1	1536.1
PS3.3	-	-	-	-	PS3.3	90.9	23.7	2750.3	1536.1

q20 - q80	*Peak (kW)*		*Costs [NOK]*		**4h**	*Peak (kW)*		*Costs [NOK]*	
	Total	Boiler	Boiler	Penalty		Total	Boiler	Boiler	Penalty
PS1	100.4	35.2	2773.6	17.3	PS1	108.5	42.1	2785.6	0.0
PS2	106.4	37.1	2773.5	0.0	PS2	110.5	42.0	2785.6	262.7
PS3	98.8	35.2	2776.8	14721.2	PS3	106.0	42.0	2788.9	15517.1
PS3.1	95.2	26.3	2776.8	14721.2	PS3.1	95.7	26.29	2789.9	15517.4
PS3.2	90.9	24.9	2776.8	14720.8	PS3.2	90.9	24.98	2790.6	15560.3
PS3.3	90.9	23.6	2776.8	14720.7	PS3.3	90.9	23.66	2791.2	15679.3

Table 6-6: The six peak shaving optimisation results for the four different flexibility strictness levels.

From these results we see that peak shaving based on boiler load is possible, even when consumption is already optimised against the market price. As this is an ex-post optimisation, we are assuming that it is perfectly possible to predict peak hours. Realistically, a perfect load forecast for households is very difficult, however the outcome still gives us a general impression of what is feasible at maximum. We also see that the overall peaks for PS1 and PS2 compared to the initial day-ahead optimisation slightly increase. The newly created optimised peak hours however, do not appear immediately after the shaved initial peak hours, i.e. there is no rebound effect. Nonetheless, creating higher peaks can be controlled for and is done so in the PS3.1-3.3 optimisations discussed below.

The difficulty in predicting exact peak hours during a year for certain grid clusters calls for an approach that limits boiler consumption more generally. Thus, we have added the PS3 optimisation, which minimises the load generally during critical hours. If all boilers cannot be set to zero, then a penalty occurs. Looking at the results, the procurement costs only increase marginally so that the optimisation can be achieved at almost no extra cost. However, boiler consumption cannot be set to zero during all the identified hours. This is visible in the second graph of Figure 6-19, which shows the results of the $20^{th}/80^{th}$ percentile optimisation. The red dots indicate the critical peak hours and do often not equal exactly zero. The blue dots are every other observation outside the critical peak hours. Nonetheless, the reduction of boiler consumption during the critical periods is large. In Table 6-6, we see that the penalty becomes higher, the stricter the approach is. While for MinMax the penalty is 210 NOK, it is 1,536 NOK for the 10th/90th percentile.

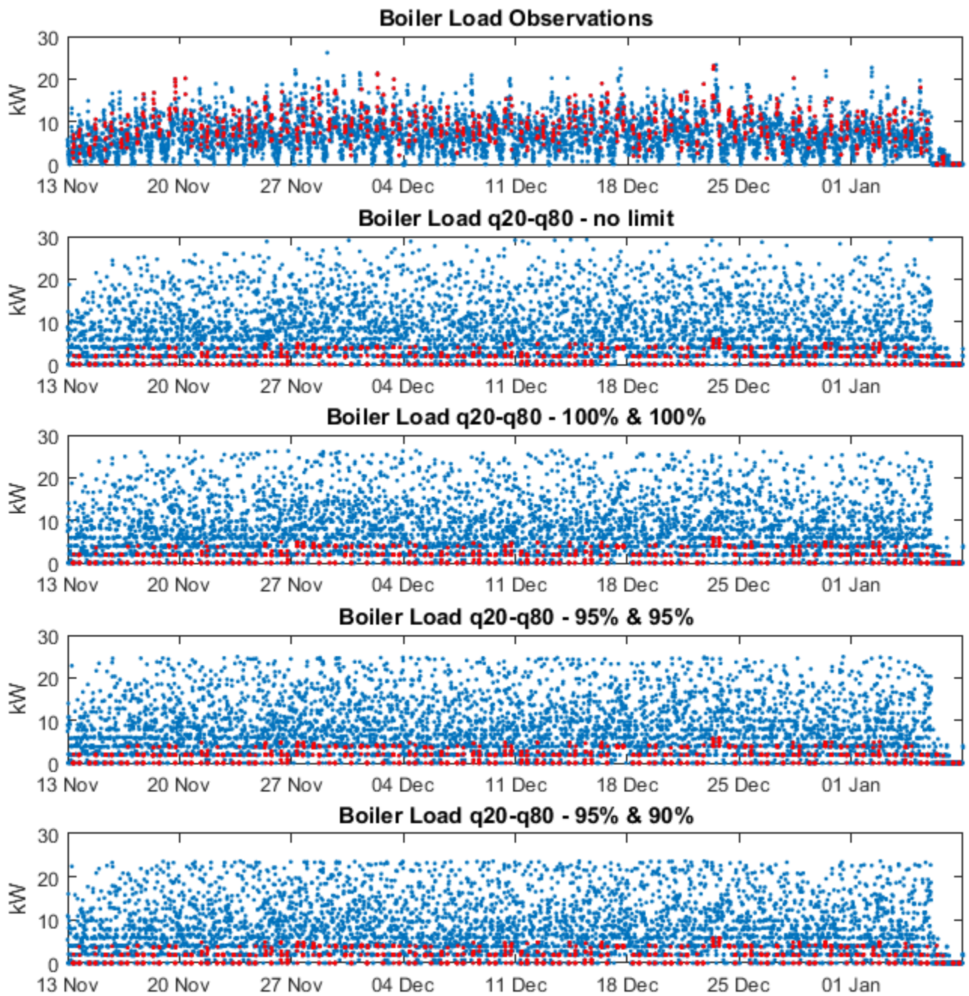

Figure 6-19: Boiler load observations and boiler load optimisation results for the optimisations PS3 to PS3.3. The red dots reflect the data points during the restricted load hours from 8 am to 10 am and from 5 pm to 7 pm, while the blue dots reflect all the other data points (15-minute resolution).

Although the overall peak slightly decreased in all the PS3 optimisations compared to the market price optimisation result, the maximal peak is still above the overall peak of the observations (96 kW). Therefore, a limit of the overall and boiler peaks is added for the scenarios from PS3.1 to PS3.3. For PS3.1 the overall limit was set to 100% of the observed overall load and the boiler load limit was also set to 100% of the observed boiler load. For PS3.2 both limits were set to 95% and for PS3.3 the overall limit was set to 95% again and the boiler limit to 90%. The third, fourth and fifth graph of Figure 6-19 perfectly show the effects the additional constraints have – where the peaks outside critical hours, represented by the blue dots, are increasingly restricted and reduced. The stricter the limits, the lower peaks over the whole period become. In Table 6-6, we also see what this means in terms of numbers. The overall peak is limited to the desired amount, whilst consumption in the morning and the evening is limited too.

From the Engene load data described in chapter 5, we know that the transformer has already overshot its nominal capacity of 25 MW by almost 2 MW in hourly averaged data or 3 MW in real time data. Considering a safety margin of 1 MW, AEN wants to avoid the transformer exceeding a load of 24 MW. This requires a load reduction of 15% during the highest peak. In PS3.2 and PS3.3 we reach an overall peak reduction of 5.3%. Assuming the results are scalable, the contribution of boiler peak shaving can already be significant. In addition, scalability would rather lead to better results than what we found for 22 households. If we also can include heating, solar panels and EVs into the DR system, a load reduction of 15% for households certainly seems feasible. What seems the crucial factor for the probability of peak-shaving is the installation, operation and maintenance cost, which will be addressed in chapter 7.

6.4.5 Limitations of the Approach

Even though we feel the newly created load profiles through the optimisation are realistic, the approach does have some limitations. The first issue is the small sample of only 22 households as representatives for the 5,380 households in Engene. The reason that only 22 out of the 100 SEMIAH households were used is the data quality. Hence, it is difficult to say on how scalable the data is.

A second limitation of the approach is the fact that the boiler temperature is not modelled. Consequently, a violation of the customer's comfort setting cannot be entirely guaranteed. However, with its sophisticated set of constraints, the sieve method allows for realistic results and makes it unlikely that not enough energy is added to the boiler system during the day. In addition, tests executed by members of the SEMIAH consortium have shown that concerns regarding temperature are not large and boilers show considerable flexibility. However, the fact that boiler temperature is not modelled could also mean that our results do not incorporate enough flexibility, as once we can accurately calculate the temperature we could find that we could leave boilers off or on for longer at certain periods, knowing the temperature is still within limits.

A third weakness of the model is the isolated view on boilers in the project. A combination of other appliances such as heat pumps or solar panels could level out many weaknesses of boilers regarding DR. On the other hand, a pointed view on only boilers gives us a strong understanding about behaviour and opportunities with boilers without the risk of mixing the effect.

In addition, a deterministic approach usually leads to a more optimistic result as compared with a stochastic one. For example, in taking the market prices as given, we are neglecting the impact the aggregator's bids in the day-ahead or ancillary service market may have on realised prices. Due to the small size of our study, this affect in negligible, however it should be considered in very large scale extrapolations or other ex-post studies, where daily procurement volumes are large enough to affect the market. To run a stochastic optimisation that creates valuable results, extensive high quality data is required. From the available data in our study, this would have been difficult.

7. Analysis

7.1 The Value of Flexibility

In the results section, we saw three potential sources of value creation for an aggregator's flexibly. Procurement cost optimisation, ancillary service participation and peak shaving. Based on these results, we are now going to assess how feasible each of the approaches is and what the numbers mean in a realistic context. Important to note is that we look at boilers as a standalone DR service. Any further integration of other devices such as heating systems, solar panels, batteries or EVs will lead to a new assessment of the situation.

7.1.1 Day-ahead Market

From our results we have seen that the gain from a pure day-ahead optimisation is between the range of 1.7% and 4.3% of total boiler procurement costs. We identified two main reasons for the low numbers. Firstly, boilers are on only for a short amount of time. This makes it difficult to profit from a very low price, unless many water heating periods can be shifted to a low price period so that it sums up. Secondly, electricity prices in Norway are not very volatile. The low volatility makes it difficult to profit from price differences. Consumption must be shifted considerably during the day, which is practically not possible with the methodology applied.

If we assume consumption and efficiency gains from our 22 households are linearly scalable and representative, we can use the numbers to calculate the total costs savings for the whole Engene cluster, as stated in Table 7-1. Extrapolating the boiler procurement costs of 2,822.7 NOK for the 22 households by the number of household costs, we receive 690,278.5 NOK for the 5,380 households.[32] Using a 2.7% cost saving rate from the $10^{th}/90^{th}$ percentile optimisation, the saving for the whole cluster would

[32] It would also have been possible to extrapolate the boiler costs by the share of total consumption of the 22 households to the total consumption in Engene. Since boiler sizes usually do not vary as much as the rest of a household's consumption, we have chosen to extrapolate simply based on the number of houses. Boiler capacity is rather proportional to the number of houses than to the total consumption.

be 18,637.5 NOK during the optimisation period and 121,143.9 NOK for the whole year. Considering the number of households, this is not huge. Since our findings are only based on 22 households, we cannot rely on the absolute numbers too much. However, the idea here is to develop a feeling for the potential of boiler DR to minimise the energy costs. From our results, we see that the potential is rather small.

Boiler Procurement Cost [NOK]	Number of households in Engene	Engene boiler procurement costs [NOK]	Cost savings [%]	Cost saving optimization period [NOK]	Cost saving yearly [NOK]
2,822.7	5,380	69,0278.5	2.7	18,637.5	121,143.9

Table 7-1: Estimation of financial benefits from the 10^{th}/90^{th} percentile day-ahead optimisation and extrapolation for the Engene cluster.

As stated in section 5.5, in Switzerland many boilers are programmed to heat during the night so that households can profit from the cheap night tariffs. Hence, we know it is possible to shift boiler consumption to other periods of the day. Therefore, it might be appropriate to have a model that allows for even larger shifts of boiler consumption in further research. To do so, it seems appropriate to model the water temperature of the boilers. Not only does it guarantee the customer's comfort limits are not violated, it also gives more flexibly to shift consumption over the day if that is feasible.

7.1.2 Reserve Option Market

The evaluation of RKOM participation is more challenging. To include all monetary benefits, we need to consider the provision of the capacity and the delivery of electricity. The calculation of the financial benefits from the capacity provision is simple. The RKOM price multiplied by the numbers of hours the power band is provided during one week (e.g. 7 x 19 if daytime). The delivery of regulating energy is more difficult. Regulating energy bids are only activated if required and for a specific time. Precisely when and for how long this happens is not published. Furthermore, it is not certain which bids are activated. The cheapest ones with the cheapest price are activated first. NordPool publishes the regulating prices and volumes for each hour but only on an aggregated level [110].

Our simulation shows that a maximum of 4 kW/week would have been accepted in the MinMax case and only 1 kW/week when using the other approaches. Assume again that we can perfectly scale our results and our households are representative for the whole of Engene. Since we have 5,380 households in Engene, we could offer 245 times more RKOM capacity if 100% of Engene is integrated in DR.[33] This leaves us with a total amount of 245 kW/week to 980 kW/week. Unfortunately, the minimum bid size is 10 MW. Thus, with only individual family boiler DR, a participation in the RKOM market is not possible. It is likely though that scaling effects will be able to increase the potential.

The profit from RKOM capacity is under 15 NOK/week for the 22 households even in the most successful optimisation. The attractive income comes from the up-regulation energy provided. Up to 135 NOK/week can be generated in the best scenario found. Scaled up this could be an interesting business case. Unfortunately, this is not the case for most of the weeks and the total income is much lower.

Considering the number of houses needed to offer 1 MWh, it does not seem attractive to participate on RKOM from a monetary perspective. As already mentioned, the situation could improve with larger scale aggregation. It will be easier to offer larger power bands on RKOM if more houses are integrated. It becomes more likely to have at least some boilers on, which can be turned off. However, without the combination of other devices, small scale boilers seem not to be able to participate at RKOM by themselves – at least under the current market framework with a 10 MW minimum lot size.

The value of flexibility could also increase if Statnett introduced a RKOM for negative power (decrease power generation or increase consumption). This would provide an extra possibility for demand-side units to sell their flexibility. Even though the service is not required in Norway now, it could become useful in the future due to, for example, an increase in wind power generation. A change in the ancillary service market now would also allow a fast reaction to new conditions within the grid of Norway or neighbouring countries.

7.1.3 Peak Shaving

The third business case considered was peak shaving. Above we ran separate optimisations for the aggregator model and the DSO model. For the evaluation of the flexibility potential, we will look at the two models combined.

[33] 5,380 households are ~245 times the 22 households for our optimisation.

From the aggregator model, we could see that it is possible to reduce the overall peak for all optimisation methods to 88 kW at almost zero cost. Also, the boiler peaks could be reduced significantly but costs were slightly higher. From the DSO model, we saw that the shaving of individual peak hours is not difficult either. Further, we could show that restricting consumption during critical hours in the morning and the evening is feasible, even while controlling for the overall and boiler peaks at the same time.

The losses on the day ahead market are for all types of peak shaving relatively low. In case a DSO would like to use a load reduction service from an aggregator, he would have to pay at least the marginal price. As an example, we can consider the PS3.3 $20^{th}/80^{th}$ percentile optimisation. The initial day ahead optimisation gave us procurement costs of 2,773.5 NOK, while the PS3.3 optimisation ended up with 2,776.8 NOK. Thus, the marginal costs of the aggregator would be 3.3 NOK to offer the PS3.3 service for the 22 households during the eight-week period. Assuming our results are scalable and representative, the service for two months for whole of the Engene cluster would cost 807 NOK.

However, the aggregator is likely to be in a monopolistic or at least not a very competitive situation when offering the service to the DSO. It is unrealistic that several aggregators will control the same group of households, especially if peak load is reduced locally. Consequently, the aggregator will charge a price that is above his marginal costs. He would estimate the DSO's benefits of peak shaving, and set a price that is just below the DSO's total costs over the investment horizon. If this follows, the flexibility prices might need to be regulated.

Overall we can sum up that on our small-scale analysis for boiler DR – day-ahead markets and RKOM do not offer huge monetary incentives. The most attractive business case is peak shaving. Not only does it seem to be relatively effective, it also comes at low costs. However, just boiler DR itself may not be sufficient. Other appliances should be added to the DR portfolio of households.

7.2 Copper or Smart Grid Investment?

In the previous chapter, we have assessed the potential that comes with boiler flexibility. Whether the DR technology can be successfully implemented, depends on the cost it comes with. Thus, we will now weigh up the benefits of DR against its investment costs.

According to AEN, the additional transformer capacity requires an investment of approximately 1 million EUR. Thus, the investment costs in DR cannot exceed that amount. To check if this is possible, we made a cost estimation for a DR system based on the SEMIAH pilot in Engene – see Table 7-2. The system includes boiler and heating DR. The heating DR is based on direct heating for three controllable rooms. The cost estimates for the devices are based on an estimation from Develco Products for large quantities.[34] The installation time depends on the electric installation in each house and is based on the experience of AEN setting up the SEMIAH pilot. The hourly rates for an electrician and technician are hourly industry average from Norway plus a 25% surcharge [111,112]. As a result, we get an installation costs of 283.6 EUR per household. Assuming 90% of the houses in the Engene cluster are integrated in the DR system, the total costs are 1.4 million EUR which leads to a loss of 0.4 million EUR. The numbers are rather optimistic and do not include the required software costs and OPEX. If we do not want to exceed the costs of upgrading the Engene transformer, only 3,917 household can be integrated into the DR system.

Description	**Costs**	**Unit**
Boiler installation material cost (Gateway, Smart Plug Mini, Smart Relay, temperature sensor)*	-95.0	EUR
Heating installation material costs (4 temperature sensors, 3 smart plugs)*	-103.6	EUR
Number of households	5380	
Installation time**	1.5	h
Share of participating households	90	%
Rate electrician***	30	EUR/h
Installation time**	1	h
Rate IT technician***	40.0	EUR/h
Total costs per house	283.6	EUR
Total costs for Engene	1'373'191.2	EUR
Investment costs new transformer**	1'000'000.0	EUR
Financial benefit from DR	-373'191.20	EUR

*Table 7-2: Costs of investments in a DR system for household flexibility, integrating boiler and heating. *Cost estimations provided by Develco Products based on large quantities **Information provided by AEN ***SalariesWIKI plus 25% surcharge* [111,112].

If we want to account for investment costs and yield, we should also consider the investment horizons. While the transformer upgrade is a matter of one or two decades, some DR devices are likely to be replaced between 4 and 6 years. Consequently, we

[34] Please note that the cost will deviate as the original listing prices are not published.

cannot look at the full transformer costs as counterweight to the DR investment. We are ignoring this since already in an optimistic case (also ignoring software costs and OPEX), it is not profitable for a DSO to invest in its own DR system to control for local peaks. One could end up with a different conclusion if global DSO grid effects are considered. If the DSO is using DR to reduce grid costs and overall peaks, he might end up with higher benefits than just local peak optimisation. In addition, the DSO will be able to lower the grid costs for his end consumers and improve its position compared to the industry's efficiency frontier. In this work, only local peaks are considered.

For the aggregator model, the same costs as stated above are valid. We can assume that the aggregator would try to receive a revenue from peak shaving relating to the transformer upgrading costs of 1 million EUR over the DSO planning horizon. Over a transformer planning horizon of say 15 years, the aggregator may have to replace the DR devices twice, trebling the above installation costs.

However, the aggregator has more possibilities to profit from a DR system through day ahead optimisation, RKOM participation, balancing cost minimisation or additional customer services. This gives him the possibilities to more easily cover his costs. Based on the boiler only example of this work, it is difficult to quantify the financial benefits of flexibility for other devices such as heating. Only with the day-ahead optimisation of boilers itself, it could be possible to cover the investment costs of 283.6 EUR of the DR system itself. Other studies, such as Vanthournot et al. [67], find cost savings on total consumption of around 10%. Over three to five years, this should be able to pay off. If these cost savings are passed on to the end consumer, the DR investment cost should be paid by them as well. However, if the households only receives rewards in other forms, the costs most probably should be covered by the aggregator. Depending on the pressure from the market and the willingness of the consumers to contribute, the aggregator might be able to pass the investment costs to the end consumers in either scenario. The Swiss storage network Tiko from Swisscom Energy Solutions follows that principal and shifts part of the installation/investment costs to its customers [113].

In a liberated market, DR and smart building services might become a standard. Consequently, aggregators or energy suppliers will be forced to offer such services to not lose all their clients to competitors. In such a scenario, the return on a DR system could become secondary and investments will need to be made regardless, in order to stay competitive.

7.3 Implications for Current Policy and Market Frameworks

As Thema [94] stated in their assessment on DR in the Nordics, regulations and markets should not be tailored to promote DR. Regulations and markets should allow the utilisation of the most efficient resources, no matter if demand or supply side. We share this point of view but would like to add that regulations and markets also should not place any unnecessary obstacles in the way of DR. Electricity markets and regulations are still based on old principles and often do not allow for much innovation. Fortunately change is due, yet at quite a slow pace.

From our point of view, an urgent topic in Norway is to implement grid tariffs for small consumers that are based on the cost-by-cause principle. In other words, the grid tariff should be based on capacity and not on energy used. Firstly, it would mean that those who create the requirement for additional grid capacity also pay for it.[35] Secondly, it would ensure that DSOs will generate revenue where investments are necessary. Thirdly, the approach provides monetary incentives for end consumers to manually or automatically adjust their behaviour so it minimises local and/or global peaks. Hence, the adjustment of grid tariffs will not promote DR directly but will lower the threshold if it is an efficient technology. From our optimisation, we saw that margins are small and every additional incentive will take some pressure from the cost side.

Besides making tariffs for small Norwegian end consumers more capacity driven, both the energy and the capacity component should be dynamic. Thus, households should pay more for capacity or energy when those resources are scare and less if there is enough available. The dynamic pricing of electricity will provide a natural incentive for households to connect their behaviour more to the wholesale market. From most energy suppliers in Norway, electricity tariffs coupled to spot prices are already available [109]. A dynamic or event based capacity component could help to reduce congestion during very critical hours. As stated in section 2.6.4, NVE has recognised the need to change grid tariff regulation and is working on a new tariff framework.

At the moment, it is almost impossible to participate in the balancing market for small end consumers. Minimum thresholds and prequalification requirements are simply not laid out for households. In order to make use of household flexibility to stabilise the

[35] Please be aware that a cost-by-cause principle also can lead to situations where certain grid users pay more for capacity, even if they are connected to a grid where capacity is not scarce. Thus, differences in grid topology can have the effect that consumers will pay more for capacity even though they are not the real drivers of the actual investment costs.

grid, new products or flexibility markets/mechanisms must be defined. Especially in a regulated industry such as DSOs, new market mechanisms are unlikely to be installed if there is no active impulse from the regulator. For instance, there could be a peak shaving market where DSOs can buy load reduction during critical hours during a day or even a week. Such a market cannot be the result of one very engaged DSO in Norway. Moreover, it needs to be a commonly developed concept from all parties involved (DSOs, suppliers, TSO and regulators).

Part of a new flexibility market concept should also be a clear definition of the market players. Especially the role and function of an aggregator has been discussed a great deal in recent years. A clear description of that role within a specific framework would remove market uncertainty and help to standardise processes and contracts. As SEDC [114] states, the current contractual situation in the Norwegian electricity market makes it difficult or almost impossible for a third party to sell flexibility services to the TSO. An aggregator would need to either work for a BRP or sign agreements with each BRP of its own clients.

New roles and functions also create new possibilities of market power. Particularly automatically controlled DR brings a high potential for market manipulation. The regulator must install control mechanisms so that suppliers, aggregators, service providers or DSOs are not able to maximise their profits at the end consumer's expense. Private households are hardly able to notice when they are systematically exploited without their knowledge or agreement. Especially if each customer gets exploited by only a small amount, it is difficult for them to detect this.

Besides paving the way for DR, NordPool should become more liquid and get closer to real time trading. This can be done in two ways: decrease the gate closure time – allow trading until e.g. 15 minutes before delivery – and increasing the time resolution of possible bids – 15 min bids instead of only 30 min. Even though there is an intraday market on NordPool and half hour products, we saw that the liquidity is very limited. Half hour products are often not traded at all. Higher resolution and shorter gate closure time can increase the exploitation of flexibility on the intraday market and hence, decrease the need for other balancing mechanisms such as RKOM. This was also recognised by Thema [94] and is the tendency on the central European power exchange EPEX [115].

As a last recommendation for the Norwegian power market, we want to outline the importance of transparency, data and information availability and standardisation. Although there has been considerable progress towards a transparent, harmonised and standardised electricity market in the last few years, there is still room for improvement. A step in the right direction is the foundation of NordReg and the ongoing process of the harmonisation of the Nordic tertiary control reserve markets. The more transparent markets are and the easier it is to access information; the more companies will consider new opportunities and drive the development of the sector. In writing this thesis, we have been continuously exposed to challenges in finding valid information or data. To some extent, this was due to language barriers but also because certain pieces were simply hard to find or not available at all.

8. Conclusion

The main focus of this thesis was to investigate whether household demand response (DR) could represent a cost-effective alternative to a 'fit-and-forget' upgrade of a distribution grid transformer – namely a 25 MW transformer in the Agder Energi Nett distribution network. In order to accurately model a prospective flexibility market for DR to operate in, we first explained the Norwegian power market in detail. The day-ahead, intra-day and ancillary service markets all represent possible avenues in which the organisation aggregating for DR could exploit the flexibility and/or reduce the procurement cost of their electricity. One significant point identified at this stage was the barriers to entry in the tertiary control reserve market – offering a minimum of 10 MW being the main issue. For new flexibility markets to be encouraged, we believe this number would have to be decreased significantly. Another is the liquidity of the intra-day market. Currently, there is a lack of liquidity such that it would not realistically be possible for any market player to exploit flexibility on this market. We expect this to change as general flexibility in the NordPool market becomes further encouraged by various regulators. We also stressed the need for effective, well-designed distribution grid tariffs that offer the appropriate incentives to unlock the maximum potential of DR. The Norwegian regulators, such as NVE, should be active in promoting the implementation of such tariffs.

We presented the numerous past evidence on DR and peak shaving and how this may translate to future cost savings in a European distribution grid. Past studies have shown that peak shaving is certainly possible through DR and many different appliances within the home have shown potential. Further studies should be conducted to focus on which appliances hold the most potential, so that these can be targeted in business environments. As of now, based on previous evidence, it is not clear to a potential new entrant in the market, such as an 'Aggregator', which appliances should be targeted for most flexibility potential. Heating, for example, seems an obvious choice, considering users effectively already allow some form of control by just setting a desired temperature – however there is not a great deal of robust evidence supporting this. Aside from studies in the U.S., where high powered air conditioning units play a factor, peak shaving results rarely show a reduction above 20%. One could argue this number could increase with larger-scale aggregation, however one could also argue that the extra users added may not be as active as the self-selected participants in virtually all DR studies. In addition, we showed how there are many expected user concerns, such as data privacy, that will likely only surmount once further, less DR interested users are on-boarded onto schemes. In Norway, however, some studies seem to suggest that users are quite happy with their smart meters and users without a smart meter have a positive sentiment towards receiving one in the future.

Future developments in technology and market frameworks were discussed and how they would affect the penetration and success of DR. There are some serious high load items, such as EVs, that could as much as triple a household's instantaneous peak demand. EVs certainly represent a challenge to distribution grid planners, however the flexibility of the installed batteries also provides an excellent opportunity for extra flexibility when plugged in. DSOs and other market players will need to make sure they consider their potentially changing role in a future electricity market and keep a close eye on technological developments – constantly evaluating their peak load impact and flexibility potential.

The SEMIAH pilot was the basis with which we developed this thesis around. The project initially provided 100 households in Norway, all with controllable hot water boilers and 4 with additional controllable panel heating. As with many other DR studies, technical and connection difficulties reduced our study to 22 boiler-only households. Maintaining the IT infrastructure to ensure up-to-the-minute data across a smart platform represents a huge future challenge for DR schemes. Aggregating the household data allowed us to analyse typical load patterns and how these coincided with the total load of the Engene cluster and external factors such as local temperature. Reviewing the proportion of boiler load in the total meter load at any one time, we saw how peaks could potentially be significantly reduced if boilers could be switched off. Sometimes turning off for less than one hour was all that was required.

We then presented two models for a flexibility market in which our household DR pilot study could exist – one that a DSO would operate and one that an aggregator would operate. We developed two models for mapping out boiler load for each household, so that this load could be optimised within bounds that could ensure user comfort post-optimisation. Presenting the aggregator model first, we showed that by optimising a hot water boiler, it is possible to reduce procurement costs in the day-ahead market by between 1.7% and 4.3%, depending on the model's flexibility constraints. We also showed that the aggregator could achieve an 8% peak load reduction at very little increase in procurement cost. This shows a high potential for

DR and the commercial viability of providing a peak shaving service to a DSO or any other interested customer.

In the reserve option market, we could offer between 1 and 4 kW each week of reserve power. Even if this sum is multiplied to represent the Engene cluster of 5,380 households, the total amount is still only between 245 kW and 980 kW per week. Set against the 10 MW minimum capacity currently required in the Norwegian reserve option market, participation is far off. One of the main problems is the availability of boilers that can be turned off during the up-regulating period, i.e. down in consumption. Larger scale aggregation could help this issue, however hot water boilers are not the best appliance to be exploited in the reserve option market, due to their less permanent requirement for constant power. Heating during the winter would provide a better alternative. Statnett introducing down regulation in the reserve option market, i.e. increase in consumption, may also improve the chances of boiler DR participation. Even if participation were possible, we found that the monetary incentives were not high. This is largely due to a very low option price for regulating power in the Norwegian market. With more unpredictable demand spikes expected in the future, from EVs and the like, we expect the need and therefore the price for regulating capacity to increase which may make it more attractive to flexibility providers. An alternative to more regulating power could be an increase in activity in the intraday market, which would also then make this market more attractive to the flexibility provider. Due to the current lack of liquidity of the Norwegian intra-day market, it was not possible for us to optimise any procurement through this market.

When the DSO controls the optimisation, from the starting point of an already cost minimised load path, we could reduce boiler usage to zero for selected local, regional and daily peaks (08:00-10:00 and 17:00-19:00) at little or no extra cost to procurement. We showed that whilst keeping daily boiler consumption low between 08:00-10:00 and 17:00-19:00, we could also achieve a peak load reduction of 5.3%, as compared with the 15% reduction currently required by Agder Energi Nett to keep their transformer 1 MW below the 25 MW capacity threshold. We see this as a significant result considering the aggregation of only 22 households with only one controlled appliance. We expect the 15% to be achievable with larger scale aggregation and more activated smart appliances, such as heating or EVs in the future.

The main limitations of our study that we identified are the small sample of houses and the lack of modelling or live testing of water temperatures. Without modelling how our new optimised paths would affect the temperature of the water, we cannot have full certainty that user comforts would not have been breached. However, we do believe our sieve method (copyright Misurio AG) to be a simple, innovative and effective approach to model boiler consumption and in our study, due to the relatively high resting water temperatures, we expect that user comfort would not have been a huge problem. Future studies should try to aggregate more households and either model the effect on water temperature or do live testing of the model with end users. Introducing extra smart appliances, particularly heating in Scandinavian studies, would be very useful. Any future studies should place very high importance of maintaining excellent connections between the smart infrastructure, to ensure as much high quality data as possible is available.

We finally summarised our results, putting them in a real-world context and attempting to answer the question of whether smart grids were a better and/or more cost-effective alternative to a transformer upgrade. We showed how it would be expensive for Agder Energi Nett to fund the entire roll-out of a household DR scheme. Although the value of this DR investment could extend beyond avoiding or delaying investment in one transformer, the relatively short life span of DR equipment versus a transformer makes this option seem quite unaffordable. Buying flexibility from an aggregator appears to be a much more cost-effective option. The pricing of this flexibility is still unclear, particularly as we do not know how many other customers the aggregator may have, what their optimisation objectives will be, and how these may conflict or complement with that of Agder Energi Nett. From the results of our study, we do expect that DR will be able to deliver the required reduction in peak demand to avoid or delay the transformer investment but due to the current lack of flexibility pricing, we cannot guarantee it will provide a truly cost-effective alternative.

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Appendix

Appendix A

Results for the four different types of optimisation. The RKOM results take too much space as the could be covered here. If the detailed results are if interest, they can be provided and please contact the authors.

MinMax optimisation results

			Peak		Consumption		Cost				Performance			Price		Cost	
			Overall	Boiler only	Overall	Boiler only	Overall	Boiler only	Peak hours	Obj fct	Duration	MIP gap	Bestbound	Overall	Boiler only	Diff vs. Reference	
			kW	kW	MWh	MWh	NOK	NOK	NOK	NOK	s	%	NOK	NOK/MWh	NOK/MWh	NOK	-
	Measurements		96.0	26.0	72.608	9.640	21'082	2'822.7						290.3	292.8		
	Peak free		109.2	42.2	72.608	9.640	20'961	2'702.6	-	2'702.6	7	-	2'702.6	288.7	280.3	-120.09	-4.25%
	Minimize boiler peak																
	Peak hours reduction																
	PS1		111.3	42.2	72.608	9.640	20'962	2'702.6	-	2'702.6	7	0.00E+00	2'702.6				
	PS3		110.8	42.0	72.608	9.640	20'964	2'704.9	209.8	2'914.6	8	0.00E+00	2'914.6				
	PS2		111.0	42.1	72.608	9.640	20'961	2'702.6	-	2'702.6	7	0.00E+00	2'702.6				
44	**Limited boiler peak**		109.1	42.1	72.608	9.640	20'961	2'702.6	-	2'702.6	8	-	2'702.6			-	0.00%
42			107.2	41.9	72.608	9.640	20'961	2'702.6	-	2'702.6	8	-	2'702.6			-	0.00%
40			110.1	40.0	72.608	9.640	20'961	2'702.6	-	2'702.6	9	0.00	2'702.6			0.0	0.00%
38			110.1	38.0	72.608	9.640	20'962	2'702.7	-	2'702.7	10	1.87E-03	2'702.6			0.1	0.00%
36			108.0	36.0	72.608	9.640	20'962	2'702.8	-	2'702.8	10	4.06E-03	2'702.7			0.1	0.01%
34			109.1	34.0	72.608	9.640	20'962	2'702.9	-	2'702.9	10	7.56E-03	2'702.7			0.3	0.01%
32			107.0	32.0	72.608	9.640	20'962	2'703.1	-	2'703.1	10	9.06E-03	2'702.9			0.5	0.02%
30			105.3	30.0	72.608	9.640	20'962	2'703.3	-	2'703.3	12	4.79E-03	2'703.1			0.7	0.02%
28			103.4	28.0	72.608	9.640	20'963	2'703.7	-	2'703.7	12	7.88E-03	2'703.5			1.1	0.04%
26			101.3	26.0	72.608	9.640	20'963	2'704.3	-	2'704.3	13	7.57E-03	2'704.0			1.6	0.06%
24			99.2	24.0	72.608	9.640	20'964	2'705.0	-	2'705.0	14	9.69E-03	2'704.8			2.4	0.09%
22			97.3	22.0	72.608	9.640	20'965	2'706.2	-	2'706.2	63	9.71E-03	2'705.9			3.5	0.13%
20			97.0	20.0	72.608	9.640	20'967	2'707.9	-	2'707.9	305	1.07E-02	2'707.6			5.3	0.19%
18			95.5	18.0	72.608	9.640	20'970	2'710.7	-	2'710.7	305	1.64E-02	2'710.3			8.1	0.30%
16			93.1	16.0	72.608	9.640	20'975	2'715.9	-	2'715.9	305	3.77E-02	2'714.9			13.3	0.49%
14			94.6	14.0	72.608	9.640	20'985	2'726.1	-	2'726.1	305	7.77E-02	2'723.9			23.4	0.87%
12			95.0	12.0	72.608	9.640	21'000	2'740.6	-	2'740.6	305	5.90E-02	2'739.0			38.0	1.41%
10			infeasible														
110	**limited (overall) peak**		109.1	42.1	72.608	9.640	20'961	2'702.6	-	2'702.6	7	-	2'702.6			-	0.00%
108			107.2	42.2	72.608	9.640	20'961	2'702.6	-	2'702.6	7	-	2'702.6			-	0.00%
106			105.1	42.0	72.608	9.640	20'961	2'702.6	-	2'702.6	7	0.00	2'702.6			0.0	0.00%
104			104.0	42.0	72.608	9.640	20'961	2'702.6	-	2'702.6	7	0.00E+00	2'702.6			-	0.00%
102			102.0	42.0	72.608	9.640	20'962	2'702.6	-	2'702.6	8	3.43E-04	2'702.6			0.0	0.00%
100			99.9	42.0	72.608	9.640	20'961	2'702.6	-	2'702.6	8	5.69E-05	2'702.6			0.0	0.00%
98			97.9	42.0	72.608	9.640	20'962	2'702.6	-	2'702.6	9	5.51E-04	2'702.6			0.0	0.00%
96			96.0	42.0	72.608	9.640	20'962	2'702.7	-	2'702.7	9	3.71E-04	2'702.6			0.0	0.00%
94			94.0	44.1	72.608	9.640	20'962	2'702.7	-	2'702.7	10	4.23E-04	2'702.7			0.0	0.00%
92			92.0	42.0	72.608	9.640	20'962	2'702.7	-	2'702.7	10	1.57E-03	2'702.7			0.1	0.00%
90			90.0	41.3	72.608	9.640	20'962	2'702.8	-	2'702.8	11	4.11E-03	2'702.7			0.2	0.01%
88			88.0	42.1	72.608	9.640	20'962	2'702.9	-	2'702.9	12	0.00	2'702.8			0.3	0.01%
86			infeasible														

$10^{th}/90^{th}$ percentile optimisation results

			Peak		Consumption		Cost				Performance			Price		Cost	
			Overall	Boiler only	Overall	Boiler only	Overall	Boiler only	Peak hours	Obj fct	Duration	MIP gap	Bestbound	Overall	Boiler only	Diff vs. Reference	
			kW	kW	MWh	MWh	NOK	NOK	NOK	NOK	s	%	NOK	NOK/MWh	NOK/MWh	NOK	-
	Measurements		96.0	26.0	72.608	9.640	21'082	2'822.7						290.3	292.8		
	Peak free		104.2	39.2	72.608	9.640	21'006	2'746.7	-	2'746.7	9	-	2'746.7	289.3	284.9	-76.05	-2.69%
	Minimize boiler peak																
	Peak hours reduction																
	PS1		104.2	40.0	72.608	9.640	21'006	2'746.7	-	2'746.7	9	0.00E+00	2'746.7				
	PS3		104.2	39.1	72.608	9.640	21'009	2'749.7	1'536.1	4'285.9	12	0.00E+00	4'285.9				
	PS2		106.1	39.2	72.608	9.640	21'006	2'746.7	-	2'746.7	9	0.00E+00	2'746.7				
	PS3.1		95.6	26.3	72.608	9.640	21'009	2'749.9	1'536.1	4'286.0	14	1.31E-03	4'285.9				
	PS3.2		90.9	25.0	72.608	9.640	21'009	2'750.1	1'536.1	4'286.2	15	3.34E-03	4'286.1				
	PS3.3		90.9	23.7	72.608	9.640	21'009	2'750.3	1'536.1	4'286.4	15	3.67E-03	4'286.3				
44	**limited boiler peak**		106.1	39.9	72.608	9.640	21'006	2'746.7	-	2'746.7	10	-	2'746.7			-	0.00%
42			104.7	41.4	72.608	9.640	21'006	2'746.7	-	2'746.7	11	-	2'746.7			-	0.00%
40			105.1	39.3	72.608	9.640	21'006	2'746.7	-	2'746.7	12	-	2'746.7			-	0.00%
38			107.0	37.5	72.608	9.640	21'006	2'746.7	-	2'746.7	13	0.00E+00	2'746.7			-	0.00%
36			104.8	36.0	72.608	9.640	21'006	2'746.7	-	2'746.7	13	0.00E+00	2'746.7			-	0.00%
34			107.0	33.9	72.608	9.640	21'006	2'746.7	-	2'746.7	13	0.00E+00	2'746.7			-	0.00%
32			107.1	31.9	72.608	9.640	21'006	2'746.7	-	2'746.7	14	1.89E-03	2'746.7			0.1	0.00%
30			104.8	30.0	72.608	9.640	21'006	2'746.7	-	2'746.7	14	2.00E-03	2'746.7			0.1	0.00%
28			102.9	28.0	72.608	9.640	21'006	2'746.8	-	2'746.8	14	5.58E-03	2'746.7			0.2	0.01%
26			101.2	26.0	72.608	9.640	21'006	2'747.0	-	2'747.0	15	8.23E-03	2'746.8			0.3	0.01%
24			99.2	24.0	72.608	9.640	21'006	2'747.1	-	2'747.1	17	5.12E-03	2'747.0			0.5	0.02%
22			104.3	22.0	72.608	9.640	21'007	2'747.7	-	2'747.7	20	9.94E-03	2'747.4			1.1	0.04%
20			100.2	20.0	72.608	9.640	21'007	2'748.4	-	2'748.4	43	8.84E-03	2'748.1			1.7	0.06%
18			100.3	18.0	72.608	9.640	21'008	2'749.4	-	2'749.4	174	7.55E-03	2'749.2			2.7	0.10%
16			98.6	16.0	72.608	9.640	21'010	2'751.3	-	2'751.3	305	2.02E-02	2'750.8			4.7	0.17%
14			96.4	14.0	72.608	9.640	21'014	2'755.0	-	2'755.0	306	5.73E-02	2'753.4			8.3	0.30%
12			94.7	12.0	72.608	9.640	21'019	2'759.8	-	2'759.8	306	4.39E-02	2'758.6			13.1	0.48%
10			infeas														
110	**limited (overall) peak**		106.3	37.1	72.608	9.640	21'006	2'746.7	-	2'746.7	10	-	2'746.7			-	0.00%
108			106.3	37.1	72.608	9.640	21'006	2'746.7	-	2'746.7	9	-	2'746.7			-	0.00%
106			104.3	38.1	72.608	9.640	21'006	2'746.7	-	2'746.7	9	-	2'746.7			-	0.00%
104			104.0	38.1	72.608	9.640	21'006	2'746.7	-	2'746.7	14	0.00E+00	2'746.7			-	0.00%
102			101.6	37.9	72.608	9.640	21'006	2'746.7	-	2'746.7	11	0.00E+00	2'746.7			-	0.00%
100			99.8	37.8	72.608	9.640	21'006	2'746.7	-	2'746.7	11	0.00E+00	2'746.7			-	0.00%
98			97.9	37.9	72.608	9.640	21'006	2'746.7	-	2'746.7	14	7.66E-05	2'746.7			0.0	0.00%
96			95.9	36.2	72.608	9.640	21'006	2'746.7	-	2'746.7	14	5.30E-04	2'746.7			0.0	0.00%
94			94.0	37.2	72.608	9.640	21'006	2'746.7	-	2'746.7	15	6.36E-04	2'746.7			0.0	0.00%
92			91.9	37.8	72.608	9.640	21'006	2'746.7	-	2'746.7	13	4.99E-04	2'746.7			0.0	0.00%
90			90.0	39.8	72.608	9.640	21'006	2'746.7	-	2'746.7	14	9.85E-04	2'746.7			0.1	0.00%
88			87.9	38.2	72.608	9.640	21'006	2'746.8	-	2'746.8	16	0.00	2'746.7			0.1	0.00%
86			infeasible														

$20^{\text{th}}/80^{\text{th}}$ percentile optimisation results

		Peak		Consumption		Cost				Performance			Price		Cost	
		Overall	Boiler only	Overall	Boiler only	Overall	Boiler only	Peak hours	Obj fct	Duration	MIP gap	Bestbound	Overall	Boiler only	Diff vs. Reference	
		kW	kW	MWh	MWh	NOK	NOK	NOK	NOK	s	%	NOK	NOK/MWh	NOK/MWh	NOK	-
	Measurements	96.0	26.0	72.608	9.640	21'082	2'822.7						290.3	292.8		
	Peak free	102.3	35.2	72.608	9.640	21'032	2'773.5	-	2'773.5	8	-	2'773.5	289.7	287.7	-49.25	-1.74%
	Minimize boiler peak															
	Peak hours reduction															
	PS1	100.4	35.2	72.608	9.640	21'032	2'773.6	17.3	2'790.9	8	-	2'790.9				
	PS3	98.8	35.2	72.608	9.640	21'036	2'776.8	14'721.2	17'498.0	22	0.01	17'496.4				
	PS2	106.4	37.1	72.608	9.640	21'032	2'773.5	-	2'773.5	8	-	2'773.5				
	PS3.1	95.2	26.3	72.608	9.640	21'036	2'776.8	14'721.2	17'498.0	51	0.01	17'496.4				
	PS3.2	90.9	24.9	72.608	9.640	21'036	2'776.8	14'720.8	17'497.6	67	0.01	17'496.1				
	PS3.3	90.9	23.6	72.608	9.640	21'036	2'776.8	14'720.7	17'497.5	115	0.01	17'496.3				
36	**Limited boiler peak**	104.9	36.0	72.608	9.640	21'032	2'773.5	-	2'773.5	11	-	2'773.5			-	0.00%
34		103.2	33.3	72.608	9.640	21'032	2'773.5	-	2'773.5	11	-	2'773.5			0.0	0.00%
32		104.3	31.9	72.608	9.640	21'032	2'773.5	-	2'773.5	12	-	2'773.5			0.0	0.00%
30		101.0	30.0	72.608	9.640	21'032	2'773.5	-	2'773.5	13	0.00E+00	2'773.5			0.0	0.00%
28		99.1	27.8	72.608	9.640	21'032	2'773.5	-	2'773.5	14	0.00E+00	2'773.5			0.0	0.00%
26		100.8	26.0	72.608	9.640	21'032	2'773.5	-	2'773.5	12	9.71E-04	2'773.5			0.0	0.00%
24		97.7	24.0	72.608	9.640	21'032	2'773.5	-	2'773.5	14	0.00E+00	2'773.5			0.0	0.00%
22		97.3	22.0	72.608	9.640	21'032	2'773.5	-	2'773.5	18	2.17E-03	2'773.5			0.1	0.00%
20		94.5	20.0	72.608	9.640	21'033	2'773.7	-	2'773.7	56	5.23E-03	2'773.5			0.2	0.01%
18		97.8	18.0	72.608	9.640	21'033	2'774.0	-	2'774.0	83	4.81E-03	2'773.8			0.5	0.02%
16		97.7	16.0	72.608	9.640	21'034	2'774.7	-	2'774.7	305	8.15E-03	2'774.5			1.2	0.04%
14		96.6	14.0	72.608	9.640	21'035	2'776.3	-	2'776.3	305	2.67E-02	2'775.5			2.8	0.10%
12		infeas														
104	**limited (overall) peak**	102.4	34.3	72.608	9.640	21'032	2'773.5	-	2'773.5	8	-	2'773.5			0.0	0.00%
102		101.4	34.3	72.608	9.640	21'032	2'773.5	-	2'773.5	9	-	2'773.5			-	0.00%
100		99.0	35.1	72.608	9.640	21'032	2'773.5	-	2'773.5	9	-	2'773.5			-	0.00%
98		97.4	34.4	72.608	9.640	21'032	2'773.5	-	2'773.5	10	0.00E+00	2'773.5			-	0.00%
96		96.0	33.1	72.608	9.640	21'032	2'773.5	-	2'773.5	10	0.00E+00	2'773.5			-	0.00%
94		93.9	37.2	72.608	9.640	21'032	2'773.5	-	2'773.5	11	0.00E+00	2'773.5			-	0.00%
92		91.4	33.4	72.608	9.640	21'032	2'773.5	-	2'773.5	14	4.48E-04	2'773.5			0.0	0.00%
90		89.9	34.2	72.608	9.640	21'032	2'773.5	-	2'773.5	15	4.57E-04	2'773.5			0.0	0.00%
88		88.0	33.4	72.608	9.640	21'032	2'773.5	-	2'773.5	13	1.14E-03	2'773.5			0.1	0.00%
86		infeas														

4-hour optimisation results

			Peak		Consumption		Cost				Performance			Price		Cost	
			Overall	Boiler only	Overall	Boiler only	Overall	Boiler only	Peak hours	Obj fct	Duration	MIP gap	Bestbound	Overall	Boiler only	Diff vs. Reference	
			kW	kW	MWh	MWh	NOK	NOK	NOK	NOK	s	%	NOK	NOK/MWh	NOK/MWh	NOK	-
	Measurements		96.0	26.0	72.608	9.640	21'082	2'822.7						290.3	292.8		
	Peak free		106.8	41.3	72.633	9.665	21'044	2'785.6	-	2'785.6	4	-	2'785.6	289.7	288.2	-37.12	-1.31%
	Minimize boiler peak																
	Peak hours reduction																
	PS1		108.5	42.1	72.633	9.665	21'045	2'785.6	-	2'785.6	4	-	2'785.6				
	PS3		106.0	42.0	72.633	9.665	21'048	2'788.9	15'517.1	18'306.0	6	0.00	18'306.0				
	PS2		110.5	42.0	72.633	9.665	21'044	2'785.6	262.7	3'048.3	4	-	3'048.3				
	PS3.1		95.7	26.3	72.633	9.665	21'049	2'789.9	15'517.4	18'307.3	10	0.00	18'306.9				
	PS3.2		90.9	25.0	72.633	9.665	21'049	2'790.6	15'560.3	18'350.9	36	0.00	18'350.9				
	PS3.3		90.9	23.7	72.633	9.665	21'050	2'791.2	15'679.3	18'470.5	306	0.02	18'467.1				
	Limited boiler peak		112.6	42.2	72.633	9.665	21'044	2'785.6	-	2'785.6	4	-	2'785.6			-	0.00%
42			109.4	42.0	72.633	9.665	21'044	2'785.6	-	2'785.6	4	0.00	2'785.6			0.0	0.00%
40			109.9	40.0	72.633	9.665	21'044	2'785.6	-	2'785.6	4	0.00	2'785.6			0.0	0.00%
38			109.1	38.0	72.633	9.665	21'045	2'785.7	-	2'785.7	5	2.77E-03	2'785.6			0.1	0.00%
36			107.2	36.0	72.633	9.665	21'044	2'785.6	-	2'785.6	5	6.88E-04	2'785.6			0.0	0.00%
34			107.5	34.0	72.633	9.665	21'045	2'785.6	-	2'785.6	6	1.93E-03	2'785.6			0.1	0.00%
32			105.8	32.0	72.633	9.665	21'045	2'785.8	-	2'785.8	7	4.74E-03	2'785.7			0.2	0.01%
30			103.9	30.0	72.633	9.665	21'045	2'786.0	-	2'786.0	6	7.55E-03	2'785.8			0.4	0.01%
28			101.7	28.0	72.633	9.665	21'045	2'786.1	-	2'786.1	7	4.73E-03	2'786.0			0.5	0.02%
26			103.6	26.0	72.633	9.665	21'046	2'786.8	-	2'786.8	6	9.40E-03	2'786.6			1.2	0.04%
24			104.0	24.0	72.633	9.665	21'047	2'787.7	-	2'787.7	11	8.76E-03	2'787.4			2.1	0.08%
22			103.7	22.0	72.633	9.665	21'048	2'788.9	-	2'788.9	15	1.00E-02	2'788.6			3.3	0.12%
20			101.6	20.0	72.633	9.665	21'050	2'790.7	-	2'790.7	189	8.16E-03	2'790.4			5.1	0.18%
18			99.9	18.0	72.633	9.665	21'052	2'792.9	-	2'792.9	305	8.41E-03	2'792.7			7.3	0.26%
16			infeasible														
110	**limited (overall) peak**		109.4	42.0	72.633	9.665	21'044	2'785.6	-	2'785.6	4	0.00	2'785.6			0.0	0.00%
108			107.5	42.2	72.633	9.665	21'044	2'785.6	-	2'785.6	4	-	2'785.6			-	0.00%
106			105.4	42.0	72.633	9.665	21'044	2'785.6	-	2'785.6	4	-	2'785.6			-	0.00%
104			103.7	43.3	72.633	9.665	21'044	2'785.6	-	2'785.6	4	0.00E+00	2'785.6			-	0.00%
102			101.8	44.1	72.633	9.665	21'044	2'785.6	-	2'785.6	5	9.04E-05	2'785.6			0.0	0.00%
100			100.0	42.1	72.633	9.665	21'044	2'785.6	-	2'785.6	5	0.00E+00	2'785.6			-	0.00%
98			98.0	43.3	72.633	9.665	21'044	2'785.6	-	2'785.6	5	2.54E-04	2'785.6			0.0	0.00%
96			96.0	42.2	72.633	9.665	21'045	2'785.7	-	2'785.7	6	1.98E-03	2'785.6			0.1	0.00%
94			94.0	43.3	72.633	9.665	21'045	2'785.7	-	2'785.7	6	2.05E-03	2'785.6			0.1	0.00%
92			92.0	43.3	72.633	9.665	21'045	2'785.7	-	2'785.7	7	1.89E-03	2'785.7			0.2	0.01%
90			90.0	44.1	72.633	9.665	21'045	2'785.9	-	2'785.9	10	3.28E-03	2'785.8			0.3	0.01%
88			88.0	44.1	72.633	9.665	21'045	2'786.0	-	2'786.0	8	0.00	2'785.9			0.4	0.02%
86			infeas														

Appendix B

Individual household boiler specifications. 20 households are displayed. Boiler temperature data for H255 and H281 was not of sufficient quality and is therefore not included.

House	Tank Size (Litres)	Idle Low Temp. (oC)	Idle High Temp. (oC)	Range (oC)	Avg. Cycle Time (Hours)	Avg. Cooling Rate (oC/hr)
H200	198	57	60	3	4	0.75
H201	198	67	72	5	5	1.25
H237	198	50	51	1	4	0.25
H242	198	50	52	2	4	0.5
H243	198	64.5	65	0.5	1.2	0.125
H251	198	43	46	3	4	0.75
H263	198	52	56	4	5	1
H264	198	54	58	4	3	1
H265	198	64	67	3	4	0.75
H267	198	66	69	3	2	0.75
H273	198	56	62	6	4	1.5
H276	198	43	46	3	9	0.75
H280	198	61	65	4	2	1
H282	198	61	63	2	4	0.5
H285	198	52	55	3	4	0.75
H289	198	67	73	6	7	1.5
H291	198	47	63	16	3	4.25
H294	198	45	47	2	4	0.5
H295	198	56	60	4	6	1
H296	198	42	45	3	2.25	0.75