The potential of residential demand response to reduce losses in an urban low-voltage distribution grid

REINOUT DAELS
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“The purpose of education is to replace an empty mind with an open one.”

Malcolm Forbes
Abstract

Demand response (DR) has been widely documented as a potential solution for several challenges the electrical power system is facing, such as the integration of intermittent renewable electricity generation and maintaining system reliability under a rapid, global electrification. While lots of research has been done into different market designs and tariffing methods, less work is available on the implications of demand response on power grid operation, especially for the low voltage side. The purpose of this thesis is to estimate the impact of a demand response program on the power losses in the low-voltage distribution network. The thesis will also contribute to the, currently limited, knowledge base on practical implementation of demand response by evaluating the outcome of a real-life DR pilot project. This pilot is part of smart cities development project ‘Stockholm Royal Seaport’ (SRS) in the east of Stockholm.

The study compared the consumption behaviour of around 400 reference consumers with a group of 154 DR enabled apartments, that are provided with an hourly varying electricity tariff. The goal was to evaluate what percentage of daily consumption is being shifted from peak to off-peak hours by the active consumers in response to the price signal, using hourly metering data collected between the 1st of January and the 22nd of March 2017. During this period, grid measurements were also collected from the SRS smart grid and used to estimate the technical power losses in the low-voltage distribution network. By combining the daily load shift of the DR consumers and the observed daily power loss fraction in the grid, an estimation was made of the impact of the demand response on the grid losses. A simulation model was also proposed, and used to simulate the effect of load shift on losses in a given grid situation.

It was found that the DR apartments overall exhibit a load shift of 2.8% of daily electricity consumption towards peak hours, and have a lower average load factor (0.57 versus 0.62 for the reference group). This could either mean that the price signal does not sufficiently manage to change load behaviour, or that the reference group was not representative. However, a strong variation in average load shift was observed amongst the individual DR apartments, ranging from -16% (shift towards peak hours) to 7%. Especially the most electricity consuming apartments showed positive load shifts. No direct influence of the load shift on the level of grid losses was found. This could be due to a too small amount of DR consumers in the grid or confounding factors such as variations in power factor and load size. To circumvent this problem, the simulation model was used to calculate loss reductions for several possible reference consumer groups and their possible reactions to a price signal. It was found that in the SRS project, the potential for loss reductions is limited because the reference group are already ‘good’ consumers. The maximum loss reduction would be around 4%. For grids with severe peak consumption however, optimal loss reductions from load shifting up to 25% were found.

The key take-away is that, while the technical potential for loss reduction is considerable in grids with strong peak loads, more research is needed to identify incentives that effectively manage to make households change their consumption behaviour. More work should also be done to find methods that can correctly evaluate load shifts.

Keywords: demand response, smart distribution grid, power loss, DSO
Sammanfattning

Efterfrågeflexibilitet (DR) har i stor utsträckning setts som en möjlig lösning för flera utmaningar som elsystemet står inför, till exempel integration av intermittent förnybar elproduktion och för att upprätthålla tillförlitligheten i elsystem under en snabb, global elektrifiering. Medan mycket forskning har gjorts i olika marknadslösningar och tarffsystem är mindre arbete tillgängligt om konsekvenserna av efterfrågeflexibilitet på elnätet, speciellt för lågspänningsidan. Syftet med detta examensarbete är att uppskatta inverkan av ett efterfrågeflexibilitetprogram på förluster i lågspänningsdistributionsnätet. Rapporten kommer också att bidra till den för närvarande begränsade kunskapsbasen om praktisk genomförande av efterfrågeflexibilitet genom att utvärdera resultatet av ett verkligt DR-pilotprojekt. Denna pilot är en del av ett utvecklingsprojekt för smarta städer "Stockholm Royal Seaport" (SRS) i östra delen av Stockholm.


Det konstaterades att DR-lägenheterna totalt sett uppvisar en lastförflyttning på 2,8 % av det dagliga elförbrukning mot höglasttimmar, och har en lägre genomsnittlig lastfaktor (0,57 mot 0,62 för referensgruppen). Detta kan antingen betyda att prissignalen inte lyckas tillräckligt med att ändra förbrukningsbeteende eller att referensgruppen inte var representativ. En stark variation i genomsnitt lastförflyttning har emellertid observerats bland de enskilda DR-lägenheterna, från -16 % (flyttning till höglasttimmar) till 7 %. Speciellt de mest elförbrukande lägenheterna visade positiva lastförflyttningar. Inget direkt inflytande av lastförflyttning på nätförlusterna hittades. Detta kan bero på en för liten mängd DR-konsumenter i nätet eller andra faktorer som variationer i effektfaktor och belastningsstorlek. För att kringgå detta problem användes simuleringsmodellen för att beräkna förlustreduktioner för flera möjliga referenskonsumtionsgrupper och deras eventuella reaktioner på en prissignal. Det konstaterades att potentialen för förlustreduktioner är begränsad i SRS-projektet eftersom referensgruppen är redan "bra" konsumenter. Den maximala förlustreduktionen skulle vara omkring 4 %. För nät med hög topplast hittades optimala förlustreduktioner från lastförflyttning upp till 25 %. Den viktigaste slutsatsen är att medan den tekniska potentialen för förlustreduktion är stor i nät med hög topplast så krävs det mer forskning för att identifiera incitament som effektivt lyckas få hushållen att förändra sitt konsumtionsbeteende. Mer arbete bör också göras för att hitta metoder som korrekt kan utvärdera lastförflyttningar.
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<tr>
<td>DSO</td>
<td>Distribution System Operator</td>
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<td>SRS</td>
<td>Stockholm Royal Seaport</td>
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<tr>
<td>DR</td>
<td>Demand Response</td>
</tr>
<tr>
<td>Ei</td>
<td>Energimarknadsinspektionen</td>
</tr>
<tr>
<td>LS</td>
<td>Load Shift</td>
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<tr>
<td>LF</td>
<td>Load Factor</td>
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<tr>
<td>MV</td>
<td>Medium Voltage</td>
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<tr>
<td>LV</td>
<td>Low Voltage</td>
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<tr>
<td>OPEX</td>
<td>Operational Expenses</td>
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<tr>
<td>CAPEX</td>
<td>Capital Expenses</td>
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<tr>
<td>RTU</td>
<td>Remote Terminal Unit</td>
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Chapter 1

Introduction

1.1 Background

This master thesis is part of the academic component of the Stockholm Royal Seaport project. Stockholm Royal Seaport (SRS) is an urban development area in the eastern part of Stockholm. It is the largest of its kind in Sweden, and it aims to meet the city’s growing housing needs while setting an international example for sustainable urban development. The district will consist of a mix of private homes, businesses, services, amenities and a ferry port. Promoting environmental sustainability is for example done by investing in energy efficiency, waste management and phasing out all fossil fuels used in the district by 2030. The geographical situation of the SRS area in the city of Stockholm is shown in Figure 1.1.

Part of the effort to become more energy efficient is done by introducing smart grid concepts in the electrical distribution grid in the area. The smart grid aims to integrate multiple components in the distribution network such as active consumers, decentralized renewable production, electric vehicle charging and energy storage. Demand response plays an important role in the development of the smart grid. Dynamic electricity prices and environmental signals are currently provided to a group of voluntary households in the area as part of a pilot project. They are expected to shift flexible loads from peak hours to off-peak hours in response to these signals. Smart washing machines and tumble dryers will be provided to those active households to facilitate shifting load over time. The use of demand side flexibility

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For more information on Stockholm Royal Seaport, see: [http://www.stockholmroyalseaport.com/](http://www.stockholmroyalseaport.com/)

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FIGURE 1.1: The geographical situation of the Stockholm Royal Seaport area in the city of Stockholm (marked in blue).
could improve the efficiency of the system. This thesis will mainly focus on one of the potential benefits: reducing grid losses.

The Urban Smart Grid Program in Stockholm Royal Seaport is a joint initiative by Ellevio, ABB, Ericsson, Electrolux, KTH, Swedish Energy Agency and other partners. This master thesis project will be a collaboration between KTH and Ellevio, the local distribution system operator (DSO) for the SRS grid.

### 1.2 Objectives

The thesis will evaluate the demand response pilot in the SRS project, mainly from the point of view of the distribution system operator (DSO). The overall goal is to assess whether demand response (DR) projects are an attractive opportunity for a DSO, and quantify the potential benefits. The focus will mainly be on one of the expected outcomes of introducing DR: reducing the power losses in the distribution grid. The part of the grid that will be analysed is the low-voltage part that makes up the last step towards final consumers, including the secondary substation and its outgoing secondary power lines towards the loads. A big part of the thesis will consist of an analysis of the actual loss reductions in the SRS grid with active apartments, but simulations will also be done to estimate the loss reduction under different circumstances. The central research question of this thesis will therefore be:

> What is the potential contribution of residential demand response to reduce power losses in the low-voltage distribution grid?

To be able to answer this question, several subquestions will have to be answered first:

- What are the consumers’ reactions to the price signal?
- Is there a significant shift of load from peak to off-peak hours due to DR?
- How can the losses in the SRS grid be quantified?
- Is there an influence of the DR on the loss levels observed?

To further investigate the value of demand response for the DSO, an estimation of potential cost reductions from demand response will be made. The last research question is therefore:

> What are the economic incentives for a DSO to introduce demand response?

The answer to this question will include an evaluation of incentives put in place by the Swedish electricity market regulator Ei to promote efficient grid operation. The outline of the report will more or less follow the order of the questions listed here.

### 1.3 Methodology

A major part of this thesis will consist of an ex-post evaluation of the DR-pilot in Stockholm Royal Seaport in the first months of 2017. First of all hourly metering data of the ‘smart apartments’ and a group of reference customers will be used to check whether or not a significant change in behaviour of the DR consumers is observed. The main focus there will be the possible shift of electricity consumption...
from peak to off-peak hours by the DR consumers in response to the price signal. Secondly, a model will be proposed to calculate the different loss components in the low-voltage distribution grid. This model will be applied to the smart grid measurements from the SRS grid and integrated in a simulation model to simulate the grid behaviour in various scenarios. The results from the load shift and power loss calculations will then be used to see what the impact of the size of the load shift on the loss level could be. Results of the calculation from the SRS grid will be complemented with simulations made for a fictitious grid to be able to assess the impact of different circumstances and customer reactions. Finally the results from this impact assessment can be used to make an estimation of possible cost reductions for both DSO and consumers due to grid efficiency improvements from demand response.

The smart grid data was provided by distribution system operator Ellevio AB. Quarterly grid measurements are stored in structured .csv-files and uploaded daily to an FTP server, where they were accessed for use in this master thesis. The data used for this report were collected between the 1st of January and 17th of May 2017, although not all measurements are available over this whole period. The exact availability of data is discussed in detail inside the report. All data were imported and processed in R, a programming language used for data analysis, statistical computing and data visualisation.

1.4 Relevance

Driven by the need for a more environmentally sustainable energy provision, the European electricity system is facing the complex challenge of mitigating its environmental impact without jeopardizing affordability. With its ‘2020 climate & energy package’, the EU set out three targets for its energy system in the year 2020: a 20% cut of green house gas emissions compared to the 1990 level, a share of 20% from renewables in the energy production and an improvement of 20% in overall energy efficiency [9]. Along with these targets a set of binding legislation was introduced to ensure that member states contribute to meeting these targets. Demand response has the potential to contribute to achieving all of these targets. Through increasing the utilization level of the existing grids, their efficiency could be drastically improved, and the alleviation of peak system loads has the potential to reduce the need for costly and polluting fossil peak power generating plants. By unlocking the use of demand side flexibility, demand response could also facilitate the integration of intermittent renewable energy sources, such as wind and solar power, into the electricity system. This thesis is mainly aimed at two important actors in the implementation of demand response: the distribution system operator and national regulating authorities.

For distribution system operators
The roll-out of smart meters is essential for a successful implementation of demand response programs. Their automated monitoring and control functions allow the use of demand-based tariffs or direct load control schemes. In most of the member states where a roll-out has taken place (such as Sweden) or is planned, the DSO is

\[ \text{More information about R can be found on https://www.r-project.org/}. \text{ For this thesis the free, open-source R programming environment RStudio was used. It can be downloaded from https://www.rstudio.com/products/RStudio/}. \]
responsible for the smart meter deployment and operation. This represents a significant capital investment from their part. It is therefore important that different ways to extract value from these smart meters are explored. Demand response is one of these possible ways. This thesis will try and assess the impact of a price-based demand response program on the efficiency of the low-voltage distribution grid. The potential system efficiency improvements will also be translated into monetary values based on current Swedish distribution tariff regulation. The results can serve as an indication whether or not demand response is an interesting opportunity for the DSO.

For national regulating authorities
The energy efficiency directive, part of the aforementioned ‘2020 climate & energy package’, states that all member states have to ensure that national energy regulatory authorities provide incentives for grid operators to implement energy efficiency improvement measures in the context of the continuing deployment of smart grids [24]. In 2016, the Swedish electricity market regulator (Ei) has implemented new incentives in the distribution tariff regulation to motivate DSOs to further invest in the efficiency of their grids. With the results of possible efficiency improvements from demand response, this thesis will evaluate the potential size of these new incentives for both the DSO and the consumers. The result can be used by regulators to estimate the impact of this new regulation and to further improve the incentives for grid efficiency.

1.5 Limitations

Because the analysis in this master thesis relies heavily on data analysis, the main limitations are related to this. The research presented in this report was conducted from January to May of 2017. Most conclusions are drawn based on household consumptions and smart grid data measured over this period. Metering data of the smart apartments was only available from January to March. Analysis of this relatively short time frame creates some limitations on its accuracy. First of all, there could be seasonality effects playing in the consumption behaviour and grid losses over periods longer than the one analysed. January was also when the owners started moving in to the smart apartments, which could cause a transition period in which the households’ consumption patterns are still changing. They might also need some time to get familiar with the demand response and the smart appliances, so that it takes some time for them to really start shifting loads according to the price signal.
Chapter 2

Background

This section will give an overview of the context of this master thesis and discuss some topics that are important to fully understand the work presented in this thesis. The first section will talk about the power system, the different sources of grid losses and what can be done to reduce these losses. The second section will introduce the concept of demand response, list the different types of DR implementations and provide some more information about the set-up of the demand response pilot in the SRS project. The second section will also summarize the results from other DR pilots that were found in literature. The third and final section will give an overview of the regulation that is relevant for the potential cost reductions from DR for the DSO.

2.1 The electric power system

The electric power system is designed to transport electrical energy from the generators that produce the energy (nuclear power plants, gas-fired power plants, wind turbines...) to the loads that consume it. The power system is divided into different parts with different responsible system operators. The electrical transmission system comprises the higher voltage levels, and is meant to transport bulk amounts of electrical energy from generating facilities towards load centers, such as cities or large industrial centers. The part of the power system at voltage levels below the transmission system is referred to as the distribution system. The distribution system takes off the power from the transmission system in a substation. There, the power of all incoming feeders is concentrated in busbars, and then distributed to the outgoing feeders [28]. Usually, substations also contain step-down transformers to lower the voltage of the incoming power to the voltage level of the grid that it is feeding. The distribution system generally consists of at least two voltage levels: a medium and a low voltage grid. Most consumers, such as households, services and businesses, are connected on the low voltage part of the system (230/400V). However, some larger industrial loads might be connected on the medium voltage grid. The structure of a typical electric power system, starting at the power plants producing electric energy which is then transported over the transmission and distribution system to the residential consumers, is given in Figure 2.1. The transmission and distribution grid are usually operated by different entities, called respectively the Transmission System Operator (TSO) and the Distribution System Operator (DSO).

2.1.1 Losses in the electric power system

Each of these different stages in the electrical power system introduce energy losses. The average total electric power transmission and distribution losses (as percentage of electricity production) over the years in Sweden is given in Figure 2.2. In 2017,
Chapter 2. Background

FIGURE 2.1: Illustration of the structure of an electric power system [8].

FIGURE 2.2: Electric power transmission and distribution losses in Sweden, as % of electricity production [2].

this average loss fraction equalled 4.8 % [2]. This thesis will only account for technical losses, and non-technical losses such as energy theft or metering errors will be omitted in this analysis. The (technical) losses can generally be divided into two larger groups: no-load losses (or 'core-losses') and load losses (or 'line-losses'). The no-load losses originate in the iron cores of the transformers in the electricity grid. They are mainly caused by eddy currents in the core and the hysteretic behaviour of iron under the changing magnetic field in the transformer. The no-load losses appear when the transformer is energized, and are further independent of the load applied to the transformer. The no-load losses are the dominant losses at low system loads. The other type of losses are the load losses. These are the ohmic losses that appear in all conducting parts of the power system, such as power lines and transformer windings. These resistive losses increase exponentially with the current through the conductor. For this reason, the load losses will be the dominant loss component at high system loads. Typical values for the different loss components in a distribution grid are given in Table 2.1.

2.1.2 Reducing losses

Each stage of the electric power system introduces losses. Therefore even small improvements in efficiency of a grid element may accumulate to big differences in the upstream parts of the grid. All loss avoided at the customer end of the grid results
2.1. The electric power system

<table>
<thead>
<tr>
<th>Grid component</th>
<th>Typical Urban</th>
<th>Typical Rural</th>
</tr>
</thead>
<tbody>
<tr>
<td>Primary distribution lines</td>
<td>0.9</td>
<td>2.5</td>
</tr>
<tr>
<td>Distribution transformer no-load</td>
<td>1.2</td>
<td>1.7</td>
</tr>
<tr>
<td>Distribution transformer load</td>
<td>0.8</td>
<td>0.8</td>
</tr>
<tr>
<td>Secondary distribution lines</td>
<td>0.5</td>
<td>0.9</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>3.4</strong></td>
<td><strong>5.9</strong></td>
</tr>
</tbody>
</table>

Table 2.1: Typical losses at each stage of the distribution grid, as a percentage of energy sold [8].

in significant savings of energy production and transmission. Reducing the energy production and distribution needs lower amongst others the cost of the electrical system and can help to cut greenhouse gas emissions. That’s why it is important for utilities and society as a whole to ensure an efficient operation of the grid with minimal losses. There are lots of different ways in which utilities can reduce the losses in their networks. The basic idea behind some possible loss reducing measures will be explained in the rest of this section.

Reducing line losses

As was mentioned in the previous subsection, losses in power lines are mainly resistive of origin. For a balanced, three phase power system, the resistive power loss in a line is given by:

\[ P_{\text{loss}} = 3 \cdot R \cdot I^2, \] (2.1)

where \( R \) is the resistance of the line and \( I \) the phase current passing through it. The active power that flows through a line is given by:

\[ P_{\text{line}} = 3 \cdot U \cdot I \cdot \cos \phi, \] (2.2)

where \( I \) is again the phase current flowing through the line, \( U \) the phase voltage level of the line and \( \cos \phi \) the power factor. Using equation 2.2, the current \( I \) can be eliminated from equation 2.1 resulting in the following expression for the resistive line loss:

\[ P_{\text{loss}} = 3 \cdot R \cdot \frac{P^2}{9 \cdot U^2 \cdot \cos \phi} = \frac{1}{3} \cdot P^2 \cdot \left( \frac{R}{U^2 \cdot \cos \phi} \right). \] (2.3)

From the right hand side of this equation it can be seen that the line losses depend quadratically on the load of the line. The equation also shows what can be done to minimize the losses for a certain level of load. There are three factors than can be tweaked to reduce the loss.

The first possibility is to reduce the resistance of the line. The resistance per unit length of a conductor is simply given by:

\[ R = \frac{\rho}{A} = \frac{1}{\sigma \cdot A}, \] (2.4)

where \( A \) is the cross-section of the conductor, \( \rho \) the resistivity of the material used and \( \rho^{-1} = \sigma \) the conductivity of the material. The resistance can therefore be reduced...
by increasing the cross-section of the conductor or choosing a suitable material. Increasing the cross-section creates a trade-off between lower resistance and increase costs, since a larger cross-section means that more material is needed. To reduce the resistivity, copper could be used instead of for example aluminum. Copper however has a higher cost and increases weight of the conductors. A second way to reduce line losses is by increasing the voltage level of the line, since higher voltage means lower current for the same level of load. Increasing the voltage however will also increase insulation requirements of the line, which in turn will increase costs. This will again lead to a trade-off between reducing losses and increasing costs.

The third factor that can influence the level of losses is the power factor $\cos \phi$. The power factor indicates the fraction of the total apparent power that consists of useful, active power. The rest of the apparent power consists of reactive power, which draws current through the line but does not deliver any net energy to the load. Perfectly resistive lines have a load factor of one, meaning that all power is active. In reality however, this will never be exactly the case since all power lines have a capacitive and inductive component drawing reactive power. Also transformers, motors or electronic equipment introduce reactive power in the power system, decreasing the power factor. Luckily, there are ways for utilities to increase the power factor of the grid. One basic solution is to install capacitor banks that help to produce or absorb part of the reactive power [8]. More recently, a range of power electronic applications called STATic synchronous COMpensators (STATCOM) have emerged that help utilities to increase the power quality in the grid [31].

**Reducing transformer losses**

As was mentioned before, transformers introduce two types of losses in the system: load losses and no-load losses. The load losses consist of resistive losses in the transformer primary and secondary windings. Reducing load losses is therefore, similarly as for the line losses, mainly done by choosing a material with a high conductivity, such as copper, for the windings.

The no-load losses originate in the transformer’s core. The core of the transformer is made of a ferromagnetic material such as steel, usually made up of individual sheets. There are two main sources of core losses. The first one are eddy currents induced in the core by the changing magnetic flux, which cause ohmic losses. These eddy current losses are of the form:

$$P_{\text{eddy}} \sim \sigma d^2 f^2 B^2,$$

(2.5)

with $d$ the thickness of the core sheets, $\sigma$ the conductivity of the core material, $f$ the frequency of the power system and $B$ the magnetic induction in the core. Since the frequency of the power system is fixed, two factors two reduce eddy currents in the core remain. The first one is the thickness of the core sheets $d$. Reducing $d$ reduces eddy currents, but at the cost of increased manufacturing costs. Secondly, the conductivity of the core material can be reduced. In practice, this is for example done by alloying silicon into the core iron. The second source of core losses is the hysteresis behaviour of the core material. These losses occur because of friction in the material when the magnetic domains turn around. Proper treatment of the material during production process can help to reduce these losses. The no-load losses of the transformer scale with the size of the transformer. It is therefore important not to oversize the transformer. Choosing a transformer with a power rating much higher than required might result in no-load losses higher than
2.2. Demand response

Electrical power systems are currently in a phase of transition. Part of this transition is a paradigm shift towards more utilization of demand side flexibility. Traditionally, the balance between supply and demand is ensured by using supply side flexibility [11]. The flexibility of consumers’ power demands are traditionally only actively used for large industrial consumers at high power levels. With the advent of smart distribution systems however, there has been increasing attention for the potential use of demand side flexibility for residential consumers as well. The usage of demand side flexibility sources is what is usually referred to as demand response (DR). A demand response program tries to influence consumers to change their electricity consumption behaviour in response to a signal such as dynamic prices or incentive payments. These different types of demand response implementations will be discussed in the first subsection.

2.2.1 Types of demand response

A demand response program can be implemented in several forms. They can be divided in two large groups based on how behaviour changes are obtained: incentive-based and price-based programs [11] [16]. In price-based programs consumers react to an electricity price signal, while in incentive-based programs they receive incentive payments independent from electricity price. Both types of programs have some distinct subcategories [11] [16] [29].

Incentive-based programs (sometimes also referred to as “explicit demand response”) reward participating consumers with monetary incentives, such as participation fees.

The ways of reducing network losses mentioned in this section so far mainly deal with design issues of system elements. The way that the power system is operated, on the other hand, can have a significant impact on the losses as well. As was shown in equation 2.3, the load-losses depend quadratically on the system load. Because of this quadratic dependence, distributing the system load more evenly over time by shifting load away from peak hours should lower the total losses. This effect is illustrated in Figure 2.3. Marginal losses go from around 10% at 50% system load, up to 20% at full system load. This means that shifting load from a moment of full peak load to a moment of 50% peak load may save around 10% of the load shifted.

This assumes 25% no-load and 75% load losses.

**Figure 2.3:** Increase of average and marginal line losses with system load [8].
or bill discounts, for changing their demand at certain moments in time. The way in which the demand change is triggered and the form of the incentives can vary strongly. They can be further divided into instruction-based and market-based programs.

- In instruction-based programs, the utility or a third-party (‘aggregator’) issues requests or even direct instructions to increase or decrease consumption.
  
  1. Direct load control: these programs usually involve an aggregator as a third party, who is given direct control over some of the consumers’ appliances (e.g. air conditioning or electric vehicle charging). The aggregator can then offer the flexibility of a group of consumers on the market, and makes incentive payments to the consumers in turn.
  2. Curtailable load: here, utilities also issue requests for decreasing or increasing demand, but the end-user remains in control over their own appliances. Consumers are rewarded with bill credit or participation fees for following these requests. Failing to do so will typically result in penalty fees.
  3. Emergency demand response: consumers are given instructions to change their demand when system security is in danger. They receive incentive payments for helping restoring the system stability.

- Market-based programs rely on some form of market working to change consumer behaviour, rather than direct instructions.
  
  1. Demand bidding: in these programs, consumers can bid on load reductions in a dedicated market. If their bid is cleared they are obliged to change load accordingly.
  2. Capacity market: demand side flexibility can be used to replace or complement generation capacity reserves. Consumers offering their flexibility receive incentive payments up-front for offering their load capacity and activation payments when their capacity is called upon.
  3. Ancillary services market: consumers can bid load changes as operating reserves. When their bid is cleared, they receive an up-front incentive payment for being stand-by. When called upon, they receive an extra payment equal to the electricity spot price.

Price-based programs (sometimes also referred to as ‘implicit demand response’) try to influence consumption behaviour by providing an electricity price that varies over time, contrary to a flat rate model where the price is the same at every point in time. The underlying assumption of these kinds of programs is that consumers will move their consumption to periods with lower prices. Following are some typical types of price-based programs

1. Time-of-use tariffs (ToU): this market model divides the day in different periods in which different electricity prices are applied. Typically, these periods and prices are fixed over a longer time. A common example of ToU is a different tariff for day and night. An illustration of ToU-pricing is given in Figure 2.4a.

2. Critical peak pricing (CPP): this pricing is mostly used in the form of an extra component to a flat rate or time-of-use tariff [11]. The CPP component adds an extra component during a limited number of peak hours per year. An illustration of CPP is given in Figure 2.4b.
3. **Real-time pricing (RTP):** this tariff scheme provides a price signal that varies hourly, reflecting the changes in electricity spot price. Consumers can be notified of the price on a day-ahead or hour-ahead basis. An illustration of RTP is given in Figure 2.4c.

![Figure 2.4: Illustration of possible electricity price curves over time, in different tariff schemes.](image)

**2.2.2 Expected benefits from demand response**

Driven by the need for a more environmentally sustainable energy provision, the European electricity system is facing the complex challenge of mitigating its environmental impact without jeopardizing affordability. There are several ways in which demand response programs can contribute to facing these challenges.

**Reducing Network Losses**

As part of the ‘2020 climate and energy package’, the EU made it its goal to reduce its consumption of primary energy with 20% by 2020. This goal is to be achieved by increasing the overall efficiency of the energy system [24]. Demand response could potentially play an important role in increasing the efficiency of the electrical transmission and distribution system. The goal of most demand response programs, including the one in the Stockholm Royal Seaport, is to shift energy demand away from times of peak load. Reducing the load during these peak hours will reduce the losses in this period. Since this load is normally only shifted to another period in time rather than completely avoided, losses during other time periods will rise. However, because the power losses depend quadratically on the system load, the
percentage lost of one megawatt-hour consumed at peak load will be bigger than of one consumed during off-peak times. This was illustrated in Figure 2.3. A better distribution of the system load over time will therefore generally reduce the loss level. An important part of this thesis will be estimating the potential reduction in grid losses due to demand response.

Increasing reliability of the power system
Unavailability of the electric power system can have disastrous implications on quality of life and the economy. Demand response can help to offer system operators an extra balancing resource for the grid, by complementing the traditional use of production side flexibility with flexibility of consumption. By shifting load away from times of extreme system stress, expensive outages could be avoided. instruction based programs are expected to be the most effective type of DR for increasing system reliability, as they give system operators almost immediate control over certain loads.

Better integration of renewable energy sources in the power system
Another part of the ‘2020 climate and energy package’ consists of increasing the share of energy produced from renewable sources. By 2020, 20% of Europe’s overall energy production should come from renewable sources. To achieve this goal, all member states received individual targets for penetration of renewables in their energy consumption, ranging from 10% in Malta to 49% in Sweden [9]. If the European objectives are to be met, three quarters of the new renewable capacities will be intermittent ones, such as wind and solar power [7]. The intermittent character of these resources creates new challenges for the power system. Simply providing a sufficient level of production capacity for the expected level of demand will not always be enough to balance demand and supply, since wind and solar energy might not be available when needed. The options to cope with this uncertainty, e.g. energy storage, are currently limited and expensive [8]. Demand response might provide an answer to this problem, since it allows the system to rely also on flexibility of demand, instead of purely on flexibility of supply, as in the traditional power system.

Reducing the cost of electricity production
Generally speaking DR events happen at times of peak demand [8]. Usually, the goal is to shift demand from peak to off-peak time. The way that scheduling of electricity production plants is done follows the merit order: production of plants with the lowest marginal price is activated first, followed by increasingly expensive power production units. The most costly peak production plants are usually fossil fuelled. Shifting consumption from peak to off-peak times will therefore decrease the production of expensive peak production units in favour of cheaper base and middle load units.

Reducing emissions of greenhouse gasses
Another objective of the EU’s climate and energy package is reducing the level of emissions of greenhouse gasses (GHG) with 20% compared to the 1990 level, in order to mitigate the impact of global warming [9]. Demand response can contribute to reducing emissions of GHG’s in several ways. The first benefit of DR that was mentioned here was reducing loss levels in the electricity grid. By reducing losses, less power has to be produced to cover the same consumption. This can result in significant savings of overall primary energy, part of which consist of fossil fuels such
as natural gas and diesel. Another benefit discussed earlier was a reduction of electricity production from expensive peak production units. These peak power plants are often fossil fuelled ones, such as gas turbines or diesel engines. The load shift towards off-peak hours caused by DR can cause a strong reduction in production from these GHG emitting sources, in favour of less polluting energy sources such as nuclear and hydro power. Finally, as was already mentioned earlier, DR also allows easier integration of intermittent renewable sources such as wind and solar PV in the power system.

2.2.3 Demand response in Stockholm Royal Seaport

The demand response project in SRS includes about 154 ‘smart apartments’, which are presented with an hourly varying electricity price, announced day-ahead. This price signal reflects the electricity day-ahead spot price, and includes an extra time-of-use distribution component that increases the electricity price during peak hours. The size of this distribution tariff is 20 öre/kWh during off-peak hours and 120 öre/kWh during peak hours. There are seven hours during the day defined as peak hours: three hours in the morning (07:00, 08:00 and 09:00), and four hours in the evening (18:00, 19:00, 20:00 and 21:00). The off-peak electricity price is around 70 öre/kWh and the peak price around 150 öre/kWh. An example of what this price signal looks like during one day is shown in Figure 2.4d. In order to enable the households to act more effectively on the price signal, they are provided with some enabling technologies such as programmable washing machines and tumble dryers.

The analysis of the grid losses will focus on the low voltage residential distribution grid in the Stockholm Royal Seaport area. The 154 smart apartments are distributed across three different sites (referred to as ‘Alpha’, ‘Beta’ and ‘Gamma’) which are supplied by two secondary substations: substation ‘Jaktgatan 39’ and substation ‘Bobergsgatan 61’. These substations connect the low-voltage residential grid at 400V with the medium-voltage grid at 11 kV. Both these substations have a similar lay-out: two incoming feeders from the MV grid at the 11 kV bus bar, one step-down transformer (connecting the 11 kV and 400 V bus bar) and 22 feeders leaving the LV bus bar towards the consumers. The connection of the different smart apartments sites with the two substations is schematically represented in 2.5.

![Figure 2.5: Supply of the smart apartments by the substations 'Jaktgatan 39' and 'Bobergsgatan 61'.](image)

100 öre = 1 SEK
The temporal scope of the analysis will be the first months of 2017, since this is when the smart apartments start to be inhabited.

2.2.4 Results from previous pilot projects

In Sweden, several studies have already been carried out to investigate the impact of variable load tariffs and demand response on consumer behaviour [23]. The results from these tests were mixed. Already in 2006 a demand response pilot was started by Sala Heby Energi Elnät AB, a local DSO in the eastern part of central Sweden [4]. A group of 500 customers was subjected to a ‘demand-based time-of-use distribution tariff’ for two years. This demand based distribution tariff was made up of a fixed charge depending on fuse size, a variable charge per kilowatt that was calculated with the average of the year’s five highest meter readings (kW) during peak hours and a variable charge based on total consumption per kWh. The result was a shift of load from peak hours to off-peak hours during the summer months of 2.2% of total yearly demand in 2006 and 2.5% in 2007. During winter months, load shifts were smaller (0.3% in 07-08) or even negative (-0.1% in 06-07). A survey amongst the participating households pointed out that the participants’ attitude towards being charged a demand-based tariff was generally positive, especially when they were informed about the positive environmental impact of a demand-based tariff. Most of the customers did not fully familiarize themselves with the details of the demand-based tariff, but rather accepted the notion that it is economically advantageous to use electricity in off-peak periods.

From November 2012 to 31 October 2013, Elforsk carried out a study that compared a group of consumers exposed to a demand-based tariff in Sollentuna with a reference group in Saltsjö-boo [3]. The observed effects were assessed as fairly marginal and limited to households living in single-family houses. Surveying of the participants indicated that the demand-based tariff had a significant effect on households’ attitudes and intentions to shift electricity use from peak to off-peak hours, but that these were not reflected in their actual behaviour. There was only a weak effect of the demand-based tariff on the share of consumption during peak and off-peak hours. The potential economic savings and positive effects on the environment were found to be the most important driving forces for behavioural changes. The greatest barriers for a change in consumption behaviour are the fact that consumers perceive the impact of their individual behaviour as negligible, and that households might already consume most of their electricity during off-peak hours.

The report by Elforsk indicates that differences in behavioural change differ significantly between different housing types. They suggest that business models that aim at increasing consumption flexibility should be adapted to different categories of households. This opinion is supported by a Sweco report regarding DSO-tariffs for low-voltage customers which suggests that the optimal tariff-structure differs from grid to grid and between types of customers [23].

2.3 Regulatory framework

Until the 1980’s the electricity sector was vertically integrated, meaning that all major activities in the sector (generation, transmission, distribution and supply) were performed by the same company [20]. In an attempt to keep the electricity sector competitive in a quickly changing landscape, these vertically integrated companies
were split up into different competing companies starting from the 1990’s. However, introducing competition in the electricity sector is not always so obvious. For example, network infrastructure businesses (such as transmission and distribution of electric power) show strong economies of scale. Because of the high investment cost, splitting the network into different competing networks increases the total cost of power distribution. Therefore, network businesses are considered to be natural monopolies. There is often only one nation-wide transmission network operator, while there can be a large number of distribution network operators that are given the monopoly over a certain region. To prevent these monopolistic companies from abusing their market power, it is important that they are well regulated. This section will look into common regulation practices for DSO’s, with particular attention for those parts of the regulation that are relevant to demand response.

2.3.1 Economic regulation of monopolies

As was explained before, network infrastructure businesses are natural monopolies because of their strong economies of scale. Monopolies are characterized by a large market power that allows them to charge prices higher than what would be charged in a competitive industry. The central question of grid regulation is therefore how much these companies can be allowed to charge for their services. There are two main methods for determining a fair price for the grid operator’s services, with both some advantages and disadvantages.

In **cost-of-service regulation** (also called ‘rate-of-return’ regulation or ‘cost-plus’ regulation), the regulator sets a maximum revenue that allows the grid operator to recover its costs and earn a reasonable return on top. This was traditionally the most used regulation method to regulate utilities. The allowed revenue for the utility equals the sum of the operational costs (OPEX) and capital costs (CAPEX), which consists of depreciation expenses and a return on capital. To determine these operational and capital costs, the regulator relies heavily on the regulated utility itself. This information asymmetry is the main disadvantage of this type of regulation. Grid companies may be inclined to lie about their real costs in order to increase the revenue level and their profit. Another weak point of this regulation type is that it does not promote cost-efficiency. It gives no incentives to reduce costs of grid operation. The main advantage of cost-of-service regulation is that it allows the utility to fully recover all its costs and provides financial stability [20].

A second type of regulation, that tries to deal with the disadvantages of cost-of-service regulation, is called **incentive-based regulation**. This regulation form determines a revenue path for a certain regulatory period, typically four or five years. At the end of each regulatory period, the regulatory framework is evaluated and adapted where needed. A revenue or price cap is set over the regulatory period following the form:

\[
R_t = R_{t-1} \cdot (1 + CPI - x),
\]

where \(R_t\) is the revenue cap in year \(t\), \(CPI\) a customer price index that accounts for inflation and \(x\) an efficiency factor [20]. A similar regulation can be used based on a price cap rather than revenue cap:

\[
P_t = P_{t-1} \cdot (1 + CPI - x).
\]
The revenue or price cap is set ‘ex-ante’, meaning that there is no feedback from the real costs inside a regulatory period. This kind of regulation provides a strong incentive for the utility to increase efficiency. If the regulated company manages to increase efficiency with more than \(x\), they are allowed to keep the resulting profit gains. At the end of the regulatory period however, the regulator will adapt \(R_0\) and \(x\) to better reflect the actual costs the utility faces.

The revenue cap regulation also allows the regulator to provide incentives for the regulated firms to achieve certain performance goals. These performance goals can be implemented by introducing a quality factor \(q\) in equation 2.6:

\[
R_t = R_{t-1} \cdot (1 + CPI - x + q),
\]  

where \(q\) can be calculated based on several performance indicators, such as customer satisfaction, system reliability/availability, environmental impact etc. The main advantages of revenue cap regulation over cost-plus regulation are that it creates incentives to lower costs, it avoids the information asymmetry and it has lower costs of regulation since it is mainly an ex-ante regulation. The main drawbacks of incentive-based regulation are that the pushing for efficiency gains might result in a decline in quality of service (although this can be mitigated by including performance goals in a quality factor) and a laxer supervision of the cost structure of the regulated companies.

Around Europe today, regulators are replacing the traditional cost-plus approach by more incentive-based regulatory models. Only a very limited number of countries still allow grid operators to automatically pass through costs in their tariffs [25]. However, the transition away from cost-plus regulation is not a black and white story, and there is a wide variety of regulations being implemented, that draw elements from both cost-based and incentive-based regulatory models. An overview of what type of regulation is used throughout Europe is given in Figure 2.6.
2.3.2 The revenue-cap regulation of electricity network operators in Sweden

The Swedish electricity grid is divided into three levels depending on the voltage level: transmission level, regional or subtransmission level and distribution or local level [22]. The transmission level comprises of all parts of the grid with a voltage of 220 or 400 kV. The subtransmission grid links the transmission and distribution grids and operates at lower voltage levels than the transmission grid, usually between 130 and 40 kV. Some major industrial customers are connected to the regional level, but most consumers are connected to the local grid. The distribution grid links these consumers to the subtransmission grid at voltage levels between 20 and 0.4 kV. Sweden has one transmission system operator (TSO), Svenska Kraftnät, and about 170 distribution system operators (DSOs). The TSO operates only the transmission level of the grid. All other entities that operate power systems in Sweden are defined as DSOs [32]. The transmission and distribution of electricity are considered as natural monopolies, and are regulated by the Swedish Energy Markets Inspectorate (Ei). The rest of this section will focus on the regulation of network tariffs for DSO’s.

In 2012, an ex-ante revenue cap regulation was introduced, over a regulatory period of four years. The revenue cap is determined as the sum of the operational expenses (OPEX) and capital expenses (CAPEX). These are calculated in the following way:

- **OPEX** represents the operational costs that are regarded as acceptable for an efficient system operator by the regulator. It is not a strict reference to any actual cost structure, as would be the case in a pure “cost-plus” regulatory model [25]. Operational costs are split up into controllable and non-controllable costs.

  - **Non-controllable costs** are those costs that are considered hard to influence by the DSO. In the first regulatory period (2012-2015), these included for example feeding grid fees, the cost of purchasing energy losses and agency fees [32]. Non-controllable are completely passed through to the customers. A change in these costs will result in an identical change of the revenue cap, and will therefore not influence the DSOs profit.

  - **Controllable costs** are costs that the DSO themselves have direct influence over. These costs are not passed through to the customers. This creates an incentive for the DSO to reduce these costs, since the revenue cap remains unchanged and profits will thereby increase. To force DSO’s to make an effort to reduce controllable costs, Ei adds an **efficiency requirement**: a certain percentage with which these costs should decrease yearly. In the first regulatory period (2012-2016), the efficiency requirement was set at 1% [32].

- **CAPEX** represents the cost of capital, and is based around the concept of the **regulatory asset base** (RAB). This is a measure of the company’s investments, including fixed assets (transformers, power lines,...) plus the current assets (fuel, materials, replacement parts,..). The value of these assets can be determined in different ways: the book value, market value, reproduction cost... [20]. Once the RAB is determined, the allowed returns (or ‘asset remuneration’) can be determined by subtracting the depreciations from the RAB and multiplying with a certain rate-of-return determined by the regulator. The total regulated CAPEX is then the sum of the allowed returns and the depreciations.
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The calculation of the revenue cap is represented schematically in Figure 2.7. Table 2.2 gives an indication of the cost structure of an average European DSO [19].

<table>
<thead>
<tr>
<th>Cost driver</th>
<th>Share of total cost [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Network operations</td>
<td>34</td>
</tr>
<tr>
<td>Customer services</td>
<td>9</td>
</tr>
<tr>
<td>Local taxes and specific fees</td>
<td>7</td>
</tr>
<tr>
<td>Transmission network access fee</td>
<td>20</td>
</tr>
<tr>
<td>Network losses</td>
<td>5</td>
</tr>
<tr>
<td>Asset financing and depreciations</td>
<td>25</td>
</tr>
</tbody>
</table>

Table 2.2: Average cost structure of a DSO in Europe.

2.3.3 Changes applied from the second regulatory period

With the start of a new regulatory period in 2016, the revenue cap regulation was evaluated and changed where needed. In order to motivate DSOs to further strive for more efficient operations and to grasp the opportunities created by smart distribution grids, Ei has introduced several regulations and new incentive schemes.

The first change relates to all controllable costs. On top of the 1% per year efficiency requirement for controllable costs that applies to all, Ei introduced an extra efficiency requirement of 0.00 to 0.82% per year, specific for each DSO. Changes have also been made to the regulation of capital costs. With the start of the new regulatory period, a new method to calculate depreciation and asset remuneration has been introduced. However, the most relevant change in regulation for this thesis is in the change of the status of some of the operational costs. In the first regulatory period, the cost of purchasing energy losses and the fee paid to the feeding
2.3. Regulatory framework

grid were regarded as completely uncontrollable costs [32]. This has changed in the second regulatory period. Directive 2012/27/EU of the European parliament, regarding energy efficiency, states that member states shall ensure that grid operators are incentivized to improve the network efficiency in the context of the continuing deployment of smart grids [24]. In accordance to this law, Ei has included two new incentive schemes, one regarding the reduction of energy losses and one promoting an increase in system utilization.

Incentive to reduce energy losses

In the first regulatory period, the cost of grid losses was an entirely pass-through cost, since losses are seen as non-controllable in the short term because they are influenced by external factors such as weather. In the long-run however, grid operators do have an influence on the level of energy losses in their network. The incentive was therefore designed to reward a reduction of the percentage of losses in comparison to the company’s historical level of losses, and punish an increase likewise. The incentive to reduce network losses, $K_n$, is given by the following formula [32]:

$$K_n = \frac{1}{2} \cdot (N_{f\text{norm}} - N_{f\text{turn-out}}) \cdot E_{\text{turn-out}} \cdot P_n,$$

where:

- $N_{f\text{norm}}$ is the historical share of network losses for each DSO (2010-2013) as a percentage of the total amount of energy distributed.
- $N_{f\text{turn-out}}$ is the share of network losses for each DSO during the regulatory period (2016-2019) as a percentage of the total amount of energy distributed.
- $E_{\text{turn-out}}$ is the amount of distributed energy during the regulatory period (2016-2019).
- $P_n$ is the price per megawatt hour for network losses calculated as an average price during the regulatory period (2016-2019).

A reduction of network losses compared to historical loss levels will result in a positive incentive $K_n$ and vice versa. The factor $\frac{1}{2}$ in the equation implies that half of the gains/losses from a reduction/increase of network losses goes to the DSO, and the other half to the customer. In 2012, the majority of Swedish DSOs reported losses between three and six percent of total distributed energy [33]. Purchasing of grid losses can be done in several ways, either from the market or via fixed long-term contracts [10]. The regulated cost of network losses $P_n$ is then determined by Ei as the average cost of losses of the different DSOs, in order to consider the different purchasing types and prices. This also limits the incentive of an individual DSO to report a higher cost than in reality. In 2012, most DSOs had a cost of grid losses between 0.25 and 0.65 kSEK/MWh [33].

Incentive to increase system utilization

The power system has to be designed to handle peak loads, although this full capacity is only utilized during a limited number of hours. The larger the gap between peak and average load, the lower the system utilization. For the DSO, the incentive to increase system utilization includes, amongst others, a lower fee paid to the feeding grid, since this fee is usually determined by the peak capacity of the connection. The feeding grid fee however, is included in the regulation as a non-controllable cost. This means that a change in this fee will not affect the DSOs profits. To avoid this
Chapter 2. Background

and incentivize DSOs to increase grid utilization, the following incentive is included in the second regulatory period [32]:

\[
K_b = \begin{cases} 
L_{f_{\text{turn-out}}} \cdot |B_{\text{diff}}| \cdot E_{\text{turn-out}} & \text{if } B_{\text{diff}} > 0, \\
0 & \text{if } B_{\text{diff}} \leq 0,
\end{cases}
\]

(2.10)

where:

- \(L_{f_{\text{turn-out}}}\) is the average daily load factor, with the daily load factor defined as the average load divided by the maximum load during a day.

- \(B_{\text{diff}} = B_{\text{norm}} - B_{\text{turn-out}}\) is the saving per megawatt hour for the cost that is paid to the feeding grid.
  - \(B_{\text{norm}}\) is the feeding grid charge during the reference period (2010-2013) divided by the amount of distributed energy during the reference period.
  - \(B_{\text{turn-out}}\) is the feeding grid charge during the regulatory period (2016-2019) divided by the amount of distributed energy during the regulatory period.

- \(E_{\text{turn-out}}\) is the distributed energy during the regulatory period (2016-2019).

This means again that a reduction of the fee paid to the feeding grid will result in a positive value for the incentive \(K_b\). However, an increase in feeding grid fee will not result in a negative value for the incentive. This means that the incentive is only designed to reward the DSO, and not punish them. In contrast to the incentive for grid losses \(K_n\), there is no fixed share of the benefit that goes to the DSO. The percentage of the savings that the DSO can keep is determined by the load factor \(L_f\) that they can realise in the network. The actual cost for the feeding grid was between 20 SEK/MWh and 180 SEK/MWh for most Swedish DSOs in 2012 [33].

Apart from these two incentives to promote grid efficiency, Ei implemented a third incentive \(Q_T\) related to reliability of supply [32]. The details of this incentive will not be discussed here. The total adjustment of the revenue cap from the incentive schemes, \(Q_T + K_n + K_b\), summed over the four years of the regulatory period should not exceed 5% of the total revenue from the previous regulatory period. The total adjustment of the revenue cap is therefore given by:

\[
\text{Tot. adjustment} = \begin{cases} 
-0.05 \cdot (\text{revenue cap}) & \text{if } (Q_T + K_n + K_b) \leq -0.05 \cdot (\text{revenue cap}), \\
Q_T + K_n + K_b & \text{else}, \\
+0.05 \cdot (\text{revenue cap}) & \text{if } (Q_T + K_n + K_b) \geq 0.05 \cdot (\text{revenue cap}).
\end{cases}
\]

(2.11)
Chapter 3

Methodology

This chapter explains how the research questions that were formulated earlier (see section 1.2) will be answered. The first two subquestions will be answered in section 3.1: is there an overall load shift to off-peak hours happening with the DR consumers and what are the different reactions of the individual apartments to the price signal. The first subsections, 3.1.1 to 3.1.3, will discuss how the DR pilot project is designed and how this design can contribute to internal validity of the experiment. Afterwards, subsection 3.1.4, will show how the impact of the demand response on a household’s consumption patterns will be quantified, in order to answer the first of the two questions that were mentioned above. The final subsection will explain how clustering of individual apartments’ consumption data will be used to identify different consumer types that represent possible reactions to the price signal.

The second section of this chapter will elaborate on the calculation of losses in the power grid. In 3.2.1, the different loss components will be introduced, and how they can generally be quantified. To make an ex-post evaluation of the loss fraction in the SRS grid, these quantification methods need to be applied to measurements from the smart grid. How this will be done is discussed in 3.2.2. To be able to do more than only ex-post evaluations, the last subsection will propose a model to simulate the grid and its losses under certain circumstances. Finally, section 3.3 will identify the different costs that could be affected by DR and how they can be calculated.

3.1 Evaluation of demand response

3.1.1 Experimental design

An important part of this thesis will consist of an ex-post evaluation of the impact of the demand response program on the consumption patterns of the consumers in the Stockholm Royal Seaport project. For these types of ex-post impact evaluations, internal validity is a major concern. In general, internal validity refers to the validity of a cause-effect relationship that is established from an experiment [21]. The notion of internal validity was first introduced in social sciences, to indicate that a treatment had an actual effect on the subjects in a study [27]. There are some general rules that can be followed to arrive at internal validity, and some threats to be guarded against. The basic set-up of an ex-post impact evaluation includes one group that is subjected to a treatment, the ‘treatment group’, and one group that is not subjected to the treatment, the ‘control group’. In the context of this study, the treatment refers to the demand response program and the expected effect is the change in consumption patterns. An internally valid experiment ensures that observed effects are due to the treatment rather than due to other factors.

One possible experimental set-up is to use the treatment group pre-treatment as the
control group, also called a ‘before-after’ comparison. Behaviour before and after the treatment of the same subjects is then compared to evaluate the impact of the treatment. The impact of the treatment is then calculated as $T_1 - T_2$, with $T_1$ and $T_2$ as in Figure 3.1. The danger with this type of experiment is that the effect of changes that happen between the pre and post assessment can be wrongfully attributed to the treatment [27]. There are numerous problems that might compromise the internal validity of a before-after assessment For example, certain subjects might drop-out of the experiment (‘attrition’[21] [27]). For experiments over a longer period of time for example, the people involved might change (‘maturation’[21] [27]).

A possible way to deal with these temporal problems is using an external control group that is monitored at the same time as the treatment group. This is called a ‘between-group comparison’. The impact of the treatment is then $T_1 - C_1$, again referring to Figure 3.1. Such an experiment eliminates the threat of temporal changes in external factors. However, it introduces other threats to internal validity. Any factor, except for the treatment, that varies across the two groups can influence the outcome of the experiment leading to an under- or overestimation of the effect of the treatment. To mitigate the effect of differences between the two groups (called ‘selection differences’[27] or ‘participant assignment bias’[21]), subjects should be randomly assigned to one of both groups, out of the same population. The participant assignment bias can then be made arbitrarily small by increasing the number of participants [27]. Unfortunately, there are also threats to internal validity that even completely random assignment does not eliminate [21]. These threats are mainly related to the influence of the fact that subjects are aware that they are being monitored on their behaviour.

To address some of the problems mentioned for the ‘before-after’ and the ‘between-group’ comparisons, a combination of both methods can be used, which is called the ‘gold standard’ of experimental design [29]. It involves a treatment group and an external control group, which are both studied before and during treatment. The impact of the treatment can then be assessed as:

$$\text{Impact} = (T_1 - T_2) - (C_1 - C_2) = (T_1 - C_1) - (T_2 - C_2)$$

These two formulas of course come down to the same result, and are just two different ways of looking at the comparison.

In practice, it is not always possible to design experiments according to this ‘gold-standard’. In the case of the SRS demand response project, the treatment group consists of around 150 apartments which are subjected to the demand response. Since they move into the apartment at the start of the project, there is no
pre-treatment data available for the treatment group. That’s why a ‘between-group’ comparison is the only possible option for this experiment. A control group will have to be set up, where the subjects in the control and treatment group are randomly selected from the same, homogenous population. The composition of the control group will be discussed in the next section.

3.1.2 Reference customers

As was mentioned in the previous section, a control group will be set up in order to estimate the impact of the demand response program on the households involved. The control group has to be chosen in a way that ensures internal validity. In the rest of this report, the control group will be referred to as the ‘reference customers’ and the treatment group as the ‘SRS customers’. To ensure validity of the results of this research, the reference customers have to resemble the SRS customers as good as possible. In the ideal case, the only difference between the reference and SRS customers should be the participation in the demand response.

The control group that is chosen as the reference customers consists of around 400 households that are metered on an hourly basis for one year. There are two important characteristics that make these reference customers suitable to compare with the SRS customers. Firstly, the reference customers are also located in the Stockholm Royal Seaport area. This will ensure that the reference customers are subject to the same external factors that might influence electricity consumption behaviour, such as weather, number of daylight hours and some lifestyle elements (e.g. regular office hours, similar holidays etc.). Secondly, the reference apartments’ main source of heating is - as in the SRS apartments - district heating. This ensures that there are no major electrical heating installations that would alter the demand structure of the reference apartments substantially.

A dataset with some aggregated hourly load indicators from the 400 households was obtained from Ellevio. The dataset contains a maximum, minimum, average and median consumed volume (kWh) over all 400 households for every hour. The average consumed volume will be used as the reference load for one apartment. Using an averaged quantity over a considerable sample size (400+) should provide a good representation of a reference load profile for the SRS consumers, because of the reasons mentioned above. A sample of the used dataset is given below. All variables are expressed in kWh except for the variance (kWh²) and the number of sites measured. A one week sample of the AVE. VOL variable is given in Figure 3.1.

<table>
<thead>
<tr>
<th>timestamp</th>
<th>MAX.VOL</th>
<th>MIN.VOL</th>
<th>AVE.VOL</th>
<th>MEDIAN.VOL</th>
<th>VARIANCE.VOL</th>
<th>NO.OF.SITES</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 2017-01-01 00:00</td>
<td>2.07</td>
<td>0</td>
<td>0.29</td>
<td>0.20</td>
<td>0.09</td>
<td>422</td>
</tr>
<tr>
<td>2 2017-01-01 01:00</td>
<td>1.48</td>
<td>0</td>
<td>0.26</td>
<td>0.19</td>
<td>0.06</td>
<td>417</td>
</tr>
<tr>
<td>3 2017-01-01 02:00</td>
<td>1.50</td>
<td>0</td>
<td>0.23</td>
<td>0.17</td>
<td>0.05</td>
<td>417</td>
</tr>
<tr>
<td>4 2017-01-01 03:00</td>
<td>1.48</td>
<td>0</td>
<td>0.21</td>
<td>0.16</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5 2017-01-01 04:00</td>
<td>1.48</td>
<td>0</td>
<td>0.20</td>
<td>0.14</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6 2017-01-01 05:00</td>
<td>1.48</td>
<td>0</td>
<td>0.19</td>
<td>0.14</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure 3.1: One week sample of the average hourly load for the group of reference apartments.

3.1.3 SRS customers

The treatment group of this study consists of 154 apartments in the Stockholm Royal Seaport area that will be subjected to demand response. The electricity consumption of these households will be measured on an hourly basis starting from January 2017. Unfortunately, it is in reality difficult to randomly assign households from the SRS population to the treatment group. For this particular project, customers volunteered to participate in the demand response program. This experimental set-up has a few threats to internal validity. As was mentioned in Section 3.1.1, the main threat to validity of a ‘between-groups’ comparison is the existence of inherent differences between the two compared groups. In the SRS project, there are two foreseeable differences between the reference and the SRS customers. The first big difference is that SRS customers are moving into their apartment from the beginning of the project, whereas the reference customers have been living in their apartments for some time. The fact that SRS customers are just moving in their apartments might cause their consumption behaviour to deviate from what it would be under ‘normal’ conditions. For example, some electrical equipment (such as freezers, coffee machines,...) may not have been installed yet. The second cause of potential differences between the two groups is the creation of a self-selection bias [14]. The fact that subjects volunteer for a demand response program might for example indicate that they are more knowledgeable about the impact of their electricity consumption, and might therefore inherently pay more attention to the timing of their electricity consumption. This would cause an over-estimation of the effect of the demand response on behavioral changes. Analysis of pre demand response data of the reference and SRS customers might be used to detect a self-selection bias [14]. Unfortunately,
there is in this research no data available about the SRS customers’ consumption behaviour without demand response.

Another issue with the SRS customers is unrelated to the self-selection, but has to do with the fact that they know that they are being monitored in a research project. Subjects might be inclined to exaggerate their behaviour changes because they feel like it is expected from them, and shift more load than they would under normal circumstances. This problem is particularly difficult to eliminate since there is no way of involving a consumer in a demand response program without them knowing.

The households that make up the treatment group are divided over three buildings in the SRS area. If a distinctly different impact from the DR is discovered for these three buildings, it could be interesting to investigate which underlying factors drive the observed differences. If, for example, the most expensive apartment type shows less or more load shift than the cheaper ones, it might indicate that income level is a factor that influences the impact of DR. This falls out of the scope of this thesis, but might be an interesting suggestion towards possible future research.

The dataset available for the SRS customers consists of hourly metering data from the individual households, all collected between the 1st of January and the 22nd of March 2017. A sample of the dataset aggregated over the three different buildings (Gamma, Alpha and Beta) is given below. All measurement data are given in kWh.

<table>
<thead>
<tr>
<th>Timestamp</th>
<th>Gamma</th>
<th>Alpha</th>
<th>Beta</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 2017-01-01 00:00</td>
<td>3.65</td>
<td>12.42</td>
<td>12.33</td>
<td>28.40</td>
</tr>
<tr>
<td>2 2017-01-01 01:00</td>
<td>3.76</td>
<td>11.16</td>
<td>12.32</td>
<td>27.24</td>
</tr>
<tr>
<td>3 2017-01-01 02:00</td>
<td>3.07</td>
<td>11.19</td>
<td>11.20</td>
<td>25.46</td>
</tr>
<tr>
<td>4 2017-01-01 03:00</td>
<td>2.95</td>
<td>15.60</td>
<td>9.20</td>
<td>27.75</td>
</tr>
<tr>
<td>5 2017-01-01 04:00</td>
<td>2.45</td>
<td>23.60</td>
<td>8.79</td>
<td>34.84</td>
</tr>
<tr>
<td>6 2017-01-01 05:00</td>
<td>2.39</td>
<td>18.62</td>
<td>9.68</td>
<td>30.69</td>
</tr>
</tbody>
</table>

A one week sample of this dataset is also visualized in Figure 3.2. It is important to note that for some apartments there are some data missing. The number of apartments metered over time is shown in Figure 3.3. It can be seen that a large part of the Gamma apartments are missing in the beginning of January. This is probably because they moved in to their apartment at a later date.

![Figure 3.2: One week sample of aggregated metering data from the SRS smart apartments](image-url)
3.1.4 Impact analysis

The treatment group (SRS customers) and control group (reference customers) are now clearly defined. The next step is to analyse the metering data and assess the actual impact of the demand response program on the customers’ consumption behaviour. More specifically of interest here is their shifting of load away from peak hours. The question to be answered for this is double. The first part is to check whether a significant load shift is observed for the SRS customers. If this is the case, the second step is to investigate if this load shift is an effect of the demand response program or rather due to other (external) factors.

In this analysis, the main point is to compare load patterns and not so much the absolute load level. Therefore, both reference and SRS load profiles will be normalised before comparing them. This will allow to easily compare for example aggregated load data from customer groups of different sizes. The load value during each hour, \( L(h) \), will be normalised with the total energy consumed during that day. This gives the following formula for the normalised load during hour \( h \):

\[
L_{\text{norm}}(h) = \frac{L(h)}{\sum_{i=1}^{24} L(i)},
\]

so that a normalised load value of 0.05 for a certain hour means that 5% of the total energy consumed that day, was consumed during this hour. A one day sample of normalised load data for the reference and SRS (total apartment load) customers is shown in Figure 3.4. It can be seen that consumption of the reference apartments during evening peak on this day was higher for the SRS customers.

The expected impact of subjecting the SRS customers to the hourly varying electricity tariff, is that they will shift part of their demand during peak hours to off-peak hours. A suited measure to compare between the reference and SRS customers...
3.1. Evaluation of demand response

is therefore the normalised peak load consumption. The normalised peak load consumption of a day is calculated as follows:

\[ \frac{\sum_{h} L(h)}{\sum_{24h} L(h)} \]  

\[(3.2)\]

where \( L_h \) is the load during hour \( h \) and the peak hours include three hours in the morning (07:00, 08:00 and 09:00), and four hours in the evening (18:00, 19:00, 20:00 and 21:00). This definition of peak hours is in line with the SRS market concept, where an extra peak price component is introduced during these hours (see Figure 2.4d). A value of 0.40 of the normalised peak load for one day for example would mean that 40% of the total daily consumption was consumed during peak hours.

As was discussed in subsection 3.1.1, the impact of the demand response program can be assessed by taking the difference between \( T1 \) and \( C1 \) as in Table 3.1, here represented by the normalised peak load of the SRS and reference customers respectively. This difference will be referred to as the daily load shift \( LS_d \). The daily load shift is then given by:

\[ LS_d = 100% \cdot \left( \frac{\sum_{peak} L_{Ref}}{\sum_{24h} L_{Ref}} - \frac{\sum_{peak} L_{SRS}}{\sum_{24h} L_{SRS}} \right) \]  

\[(3.3)\]

This definition implies that a positive load shift means that load is shifted away from peak hours by the SRS customers, whereas a negative load shift signifies a shift of load towards peak hours. A large positive value of \( LS_d \) is therefore desirable in a successful demand response program. A value of 10% of \( LS_d \) would mean that the SRS customers shifted 10% of their daily energy consumption from peak to off-peak hours. The load shift of the day represented in Figure 3.4 for example equals -4.5%.
Collectively shifting loads away from peak hours by the SRS customers might cause undesirable formation of peak loads at other times. It is therefore important to introduce a second evaluation criterium: the load factor. The goal of the load factor is to represent how ‘flat’ a load profile is. The daily load factor $LF_d$ can be defined straightforwardly as:

$$LF_d = \frac{\text{mean}(L_d)}{\text{max}(L_d)}$$ (3.4)

Defining the load factor in this way implies that when the load profile becomes flatter, the load factor goes to one. When there is a more pronounced peak in the daily load profile, the load factor will go towards zero. Using the daily load samples of Figure 3.4 as an example, the SRS load gives a load factor of 0.5 whereas the reference load that day had a load factor of 0.61. This is clearly reflected in the flatter profile of the reference load. In the rest of this report, the load shift and load factor will be the two main metrics used to characterise consumption patterns. They will be calculated for the aggregated load of each of the three buildings, and it will be determined whether or not the SRS consumers differ significantly from the reference consumers as a result of the demand response tariff.

### 3.1.5 Identifying different consumer reactions

Evaluating the load shift and load factor of the different buildings gives a good insight in the differences in the consumption patterns of the different buildings. However, they work with aggregated data and might average out interesting phenomena happening at customer level. Therefore, consumption behaviour of individual apartments will be analysed as well, to see if different types of customers can be identified, who react differently to the price signal. Elements such as average load shift, load factor and peak demand times will be calculated for individual customers.

To try and identify different consumption patterns observed amongst the SRS customers, a clustering of their load profiles will be performed.

Clustering is the process of finding groups of objects so that the objects in a group will be similar to one another and different from the objects in other groups. In the context of this thesis, it will be used to try and identify different types of consumers according to their general consumption behaviour. The most widely used technique for clustering problems is the $k$-means algorithm. This algorithm partitions $m$ data points in an $n$-dimensional space into $k$ clusters, where $k$ is a set parameter. The clusters are characterised by their centers (or means), which are the $n$-dimensional means of the elements in their cluster. Each data point $p_i$ belongs to the cluster which has the center the closest to it. The goal is to find a set of cluster centers so that elements in the same cluster are ‘close’ together in the $n$-dimensional subspace, and elements from different clusters are far apart. This is done by minimizing the objective function

$$F = \sum_{i=1}^{m} || p_i - \mu(p_i) ||^2$$ (3.5)

where $\mu(p_i)$ is the cluster center closest to $p_i$ [6]. There are different widely used algorithms to solve this optimization problem. The algorithm used by default in R is the one proposed by Hartigan and Wong [17]. The working of this algorithm will not be discussed here.
The data that will be used are the individual hourly metering data between 01-01-2017 and 22-03-2017 for all 154 apartments and the reference load. The goal of the clustering is to find patterns in the load profiles and identify similar customers in this way. To make the different load profiles easier to compare, they will first be normalised with equation 3.1. This translates to a k-means problem with 155 data points in a vector space with 1,944 dimensions, one for each hour of load data. Traditional clustering methods face difficulties with highly dimensional data, most commonly the rapid degeneration of performance with increasing number of dimensions [30]. This is referred to as the curse of dimensionality. One way to overcome this problem is via ‘feature selection’. Features can be certain existing dimensions or newly created variables that are chosen to represent the original high-dimensional dataset with fewer dimensions. The k-means algorithm is then executed on the chosen features instead of on the complete data set. Reducing dimensionality via feature selection has several advantages, such as facilitating data visualization and understanding, reducing calculation times and improving performance. Since the goal here is to group customers by their consumption pattern, some possible features could be:

- Average daily load shift (see equation 3.3)
- Average daily load factor (see equation 3.4)
- Average daily peak load (normalised value)
- Average daily peak consumption (see equation 3.2)
- Usual hour of peak load (defined as the mode of all daily peak load times for each customer)

Since the peak load and peak consumption are explicitly included in the formulas for the load factor and load shift respectively, they don’t add extra information about the customers and they are better left out of the clustering. The three selected features are then the average daily load shift, the average daily load factor and the peak consumption time. Before applying the k means algorithm, the three features are normalised so that they all have an equal weight in the euclidean distance. Otherwise, the clustering would mainly identify differences in the dimension with the highest absolute values.

### 3.2 Loss calculations

#### 3.2.1 Power loss model

As mentioned earlier, the calculations will be limited to the LV-part of the distribution grid, including everything from the secondary substation up to the consumer. In the case of the SRS grid, this is the 400 V part of the grid. As mentioned before, and illustrated in Figure 2.5, the studied part of the grid includes two secondary substations connecting the 11 kV MV grid to the residential loads at 400 V. All parts of the analysed grid topology consist of three-phase AC power. Both studied substations have a very similar lay-out. On the top of the figure, the 11 kV busbar with the two incoming feeders from the medium voltage grid. The 400V busbar is pictured at the bottom, with the 22 secondary lines leaving the substation towards the consumers. Feeders one, two and three in this scheme serve only as back-up and
are not used under normal conditions. The two busbars are connected via a single transformer, indicated as T11 in the figure. The transformer type is the same for both substations. Some relevant information about the transformers used is given in Table 3.2. All feeders in the low voltage grid are of the same type. Some relevant info about the type of line used is provided in Table 3.3. Figure 3.5 shows a schematic representation of the LV grid that will be analysed. Only one substation with one of its 22 outgoing feeders is represented just for sake of simplicity. The same model applies to both the Jaktgatan and the Bobergsgatan substations.

Table 3.2: Relevant information from the transformer’s data sheet.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wiring type</td>
<td>Dyn11</td>
<td>-</td>
</tr>
<tr>
<td>Rated power</td>
<td>800</td>
<td>kVA</td>
</tr>
<tr>
<td>Rated primary voltage</td>
<td>11000</td>
<td>V</td>
</tr>
<tr>
<td>Rated secondary voltage</td>
<td>420</td>
<td>V</td>
</tr>
<tr>
<td>No-load loss</td>
<td>1170</td>
<td>W</td>
</tr>
</tbody>
</table>

Table 3.3: Relevant information from the power line’s data sheet.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rated voltage</td>
<td>1</td>
<td>kV</td>
</tr>
<tr>
<td>Conductor material</td>
<td>Al</td>
<td>-</td>
</tr>
<tr>
<td>Number of conductors</td>
<td>4</td>
<td>-</td>
</tr>
<tr>
<td>Cross section</td>
<td>240</td>
<td>mm²</td>
</tr>
<tr>
<td>Resistance</td>
<td>0.125</td>
<td>Ω/km</td>
</tr>
</tbody>
</table>

Figure 3.5: Model of the grid part that will be used for calculating losses.

The losses in the grid consist of two main parts: losses in the substation and losses in the power lines connecting the loads to the substation. The losses in the substation consist of losses in all power devices, such as busbars, switchgear, measurement devices etc. For simplicity however, only the losses from the power transformer will be included in the substation model. The origin of all power losses was
discussed in Section 2.1. In this model, the line losses in the feeders and load losses of the transformer will be approximated as completely resistive. A breakdown of the modelling of the different losses in the grid is given below.

- **Line losses**: the line losses are taken as completely ohmic. Since the system might be in unbalance, the simplified formula 2.1 can not be used. The active power loss should be obtained by summing up the power loss in each separate phase:

\[ P_{\text{loss,line}} = R_l \cdot (I_{p1}^2 + I_{p2}^2 + I_{p3}^2), \]  

(3.6)

where \( I_p \) is the phase current in each phase and \( R_l \) the resistance of the conductor. It is important to note that the resistance of the feeder is here expressed as \( \Omega/km \) (see Table 3.3), so that power losses are also expressed per unit of length. Since the line losses scale with the load in the line, it is mainly interesting to calculate losses as a fraction of the total line load, so that the losses of feeders with different loading can be compared. To be able to calculate the loss fraction, the power flow through each feeder is needed. The active power flow in a single phase is given by:

\[ P_{\text{phase}} = U_p \cdot I_p \cdot PF, \]  

(3.7)

with \( I_p \) again the phase current, \( U_p \) the phase voltage and \( PF \) the power factor of this phase. The total line power is found by summing this expression over the three phases:

\[ P_{\text{line}} = (U_{p1} \cdot I_{p1} \cdot PF_{p1}) + (U_{p2} \cdot I_{p2} \cdot PF_{p2}) + (U_{p3} \cdot I_{p3} \cdot PF_{p3}). \]  

(3.8)

Finally, the loss fraction for a feeder can be found as:

\[ \text{Line loss fraction} = \left( \frac{P_{\text{loss,line}}}{P_{\text{line}}} \right) \cdot 100\%. \]  

(3.9)

- **Transformer losses**: the transformer in the substation introduces losses in both the core and the primary and secondary windings.

  - **Core losses**, or ‘no-load’ losses, are independent of the load on the transformer. They are reported in the datasheet of the transformer and Table 3.2.

\[ P_{\text{loss,core}} = 1170W. \]  

(3.10)

  - **Winding losses** appear both in the primary and secondary windings. They can be calculated with the phase current and the winding resistance of the three phases on both sides. The secondary side of the transformer is wired in star. This means that line current and phase current are equal. The losses in the secondary windings are given by:

\[ P_{\text{loss,wind,sec}} = I_{U2}^2R_{U2} + I_{V2}^2R_{V2} + I_{W2}^2R_{W2}, \]  

(3.11)

with \( I_{U2}, I_{V2} \) and \( I_{W2} \) the line or phase currents of the three phases at the connection points of the transformer. The resistances \( R_{U2}, R_{V2} \) and \( R_{W2} \) represent the winding resistance of the different phases.

Since the primary windings are connected in delta, the line currents have to be divided by \( \sqrt{3} \) to get the phase currents. The load losses in the
primary windings are:

\[ P_{\text{loss,wind,prim}} = R_U I_{p,U1}^2 + R_V I_{p,V1}^2 + R_W I_{p,W1}^2 \]  
\[ = \frac{1}{3} \left( R_U I_{l,U1}^2 + R_V I_{l,V1}^2 + R_W I_{l,W1}^2 \right), \]

with analogous definitions of the currents and resistances as for the secondary windings, with an \( l \) in the subscript indicating line current and \( p \) indicating phase currents.

Similarly as for the feeder, it is mainly interesting to calculate transformer loss fractions rather than absolute loss numbers. The transformer loss fraction will be defined as:

\[ \text{Transformer loss fraction} = \left( \frac{P_{\text{loss,transfo}}}{P_{\text{in}}} \right) \cdot 100\% \]
\[ = \left( \frac{P_{\text{loss,wind,prim}} + P_{\text{loss,core}} + P_{\text{loss,wind,sec}}}{P_{\text{in}}} \right) \cdot 100\%, \]

where \( P_{\text{in}} \) is the power input on the primary side of the transformer.

The loss fraction that is relevant for the DSO is not that of individual components but of the entire grid. This total loss factor will be calculated as the loss factor of a single substation:

\[ \text{Total loss fraction} = \left( \frac{P_{\text{loss,transfo}} + \sum P_{\text{loss,line}}}{P_{\text{in}}} \right) \cdot 100\%, \]

where the sum symbol indicates the sum of line losses in all feeders connected to the transformer of the analysed substation. As mentioned before in this section, line losses are expressed per unit of length. Since the length of feeders might not be known, summing up feeder and transformer losses implies the assumption that the feeders are all of length 1 km. In Figure 3.6, a schematic representation of the different loss components in the grid is shown.

### 3.2.2 Data collection & model application

In traditional distribution grids in Stockholm, secondary substations are locally controlled and operated. Centralized communication is reduced to a sum alarm signal that indicates for example high transformer temperature or a tripped circuit breaker [18]. In the Stockholm Royal Seaport network, pilot projects are running to introduce smart grid concepts also at the lowest voltage levels. To this end, remote terminal units (RTU) for monitoring and control were installed at the secondary substations. The RTU registers quarterly measurements of currents, power quality data, transformer temperature and more, all reported as average, minimum and maximum
3.2. Loss calculations

The loss model described in the previous subsection will be applied to the available smart grid data to evaluate the losses. All data used was collected between the first of January and the 17th of May 2017. It should be noted however that some daily measurement reports were not yet available for certain days during this period at the time of writing this thesis. The periods were data was missing will be mentioned when discussing the results.

Since there are power measurements available of both primary and secondary side of the transformer, all transformer losses can be calculated straightforwardly by calculating the difference between primary and secondary active power. Separate modelling of the load and no-load losses is therefore not necessary here, but the model equations will still be applied to the transformer measurements. It can be a good way to validate the transformer loss model to compare the modelled losses with the ‘real’ losses that are obtained as the difference between incoming and outgoing power of the transfo. Recall from the previous section that the no-load losses are reported in the data sheet of the transformer, and the load losses are obtained from the phase currents and winding resistances. Phase current measurements from the three phases are available in the transformer datasets described earlier in this section. Winding resistances are given in Table 3.4, as reported in the data sheet of

![System architecture of the smart distribution grid tested in the SRS grid](image)

**Figure 3.7:** System architecture of the smart distribution grid tested in the SRS grid [18].

values for each 15 minutes. These measurements are communicated to Ellevio’s SCADA and office network on a daily basis. From there, the daily measurement data is uploaded to an FTP server for use by external parties. This FTP server was also used to access the data for this thesis. The complete system architecture is shown in Figure 3.7.
Table 3.4: Winding resistances of the transformer as reported in the datasheet.

<table>
<thead>
<tr>
<th>Winding</th>
<th>Resistance [Ω]</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_{UV1}$</td>
<td>0.78820</td>
</tr>
<tr>
<td>$R_{UW1}$</td>
<td>0.78760</td>
</tr>
<tr>
<td>$R_{VW1}$</td>
<td>0.78818</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Winding</th>
<th>Resistance [Ω]</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_{UV2}$</td>
<td>0.0006557</td>
</tr>
<tr>
<td>$R_{UW2}$</td>
<td>0.0006784</td>
</tr>
<tr>
<td>$R_{VW2}$</td>
<td>0.0006550</td>
</tr>
</tbody>
</table>

Table 3.5: Winding resistances of the secondary transformer windings after star-delta transformation

<table>
<thead>
<tr>
<th>Winding</th>
<th>Resistance [Ω]</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_U2$</td>
<td>0.0002236</td>
</tr>
<tr>
<td>$R_V2$</td>
<td>0.0002159</td>
</tr>
<tr>
<td>$R_W2$</td>
<td>0.0002234</td>
</tr>
</tbody>
</table>

Losses in the primary transformer windings are given by equation 3.12. The primary side of the transformer is wired in delta. This implies that the line-to-line resistance values from Table 3.4 ($R_{UV1}, R_{UW1}, R_{VW1}$) can be directly used as phase resistance values ($R_U1, R_V1, R_W1$). The winding losses can then be obtained with the measured phase currents.

Load losses in the secondary windings are calculated with equation 3.11. Since this side of the transformer is connected in star, and the resistance of the windings is only reported in delta (resistance between the different phases: $R_{UV2}, R_{UW2}, R_{VW2}$), a star-delta transformation has to be applied to obtain the resistance of the separate phases, e.g.:

$$ R_U2 = \frac{R_{UV2} \cdot R_{UW2}}{R_{UV2} + R_{UW2} + R_{VW2}} \quad (3.16) $$

$R_V2$ and $R_W2$ can be obtained with an analogous formula. The resulting values for the resistances are given in Table 3.5.

For the low-voltage side feeders leaving the substation, only current data is available. The loss model equations from the previous section will have to be used to calculate the feeder power flow and losses. Calculation of resistive losses in the feeders is straightforward. The current measurements can be simply filled in into equation 3.6. Since no power measurements are available for individual feeders, the power flow through the lines has to be calculated with equation 3.7. However, voltage and power factor measurements are not done for individual feeders. This problem can be solved using an approximation. The power factor for example could be either approximated as being always one, or transformer level measurements of power factor could be used. Similarly for the voltage, it could either be approximated as being constant or voltage measurements could be used. The results of three different approximations are given in Figure 3.8. It can be seen that the influence of fixing the power factor is relatively big compared to that of the voltage level. Therefore, the power factor measurements of the secondary transformer side will be used for
3.2. Loss calculations

3.2.3 Simulation model

Finally, a simulation model will be introduced to reproduce grid behaviour and losses under specified circumstances. This model can for example be used to complement the results of the ex-post smart grid data analysis where data is missing or to provide insights in the loss behaviour under different circumstances. This model will simulate a grid made up of one secondary substation with some outgoing secondary feeders towards apartment buildings that consist of a mix of traditional (reference) consumers and active (DR) consumers, as is the case in the SRS grid. The modelling equations will be largely the same as in the previous two subsections, except the values for loads and currents will now be calculated instead of using measurements. Essentially the same model will be used as in Figure 3.5. The substation includes the same transformer, and has a number of outgoing feeders that is parametrised by $N_F$. An overview of all the parameters of the model is given in Table 3.6. The total number of customers supplied by the substation is given by $N_C$. These customers are divided equally over all feeders, so that each feeder supplies $N_C/N_F$ apartments. The simulated grid is visualised in Figure 3.9. The main inputs to the

\[
P_{\text{line}} = 233V \cdot (I_{p1} + I_{p2} + I_{p3}) \cdot PF_{\text{out}}
\]  

(3.17)
simulation model are two normalised load profiles, one representing the reference consumers, say $P_{\text{REF}}$, and one for the DR consumers, $P_{\text{SRS}}$.

<table>
<thead>
<tr>
<th>Description</th>
<th>Symbol</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Share of active consumers</td>
<td>$f_{\text{SRS}}$</td>
<td>[-]</td>
</tr>
<tr>
<td>Power factor</td>
<td>PF</td>
<td>[-]</td>
</tr>
<tr>
<td>Households’ average daily consumption</td>
<td>$E_d$</td>
<td>[kWh]</td>
</tr>
<tr>
<td>Number of customers in the grid</td>
<td>$N_C$</td>
<td>[-]</td>
</tr>
<tr>
<td>Number of outgoing feeders from secondary substation</td>
<td>$N_F$</td>
<td>[-]</td>
</tr>
<tr>
<td>Length of feeders</td>
<td>$\ell$</td>
<td>[km]</td>
</tr>
</tbody>
</table>

The load of each feeder will represent an apartment building with a certain number of both reference and DR dwellings. The total load profile of the building is calculated by:

$$P_{\text{TOT}} = E_d \left( f_{\text{SRS}} P_{\text{SRS}} + (1 - f_{\text{SRS}}) P_{\text{REF}} \right) \frac{N_C}{N_F}, \quad (3.18)$$

where $E_d$ is the average daily energy consumption of one apartment, $\frac{N_C}{N_F}$ is the amount of apartments in the building and $f_{\text{SRS}}$ is the fraction of these apartments that participate in demand response. This total load will be used as the feeder load.
3.3. Estimation of economic incentives

from equation 3.8. For purpose of simplicity, the grid will be approximated as entirely balanced in these simulations. This allows to do all calculations in a single phase equivalent of the grid, where the total power is simply given by three times the single phase power. This assumptions simplifies equation 3.8 to:

$$P_{\text{line}} = 3 \cdot U_p I_p \cdot \text{PF},$$  \hspace{1cm} (3.19)

with $U_p$ and $I_p$ the phase voltage and current respectively and PF the power factor of the grid. With $P_{\text{line}}$ given by equation 3.18 and $U_p=233\,\text{V}$, the current can be found for a certain power factor. The line losses are then simply calculated as

$$P_{\text{loss, line}} = 3 R_l I_p^2.$$  \hspace{1cm} (3.20)

The definition of the line loss fraction is identical to equation 3.9. With the simplified approach of this simulation model, this becomes

$$\text{Line loss fraction} = \left( \frac{R_l}{3U_p^2} \right) \cdot \frac{P_{\text{line}}}{\text{PF}^2},$$  \hspace{1cm} (3.21)

where the expression between brackets is assumed to be a constant design parameter, while the other factor can vary with the grid operation.

The losses in the secondary transformer are also included in the simulation model. The secondary transformer current is first obtained as the sum of the current in all outgoing feeders. The secondary voltage $U_{p2}$ is again assumed constant at 233V. The primary phase voltage and current are found by using the winding ratio of the transformer $n$ given by:

$$n = \frac{U_{2,\text{rated}}}{U_{1,\text{rated}}} = \frac{420}{11000} = 0.0381818...$$  \hspace{1cm} (3.22)

The primary phase current and voltage are then given by:

$$U_{p1} = \frac{U_{p2}}{n} \approx 6.1\,\text{kV},$$  \hspace{1cm} (3.23)

$$I_{p1} = n \cdot I_{p2}.$$  \hspace{1cm} (3.24)

The calculation of load and no-load losses is done as before (see equation 3.10, 3.11 and 3.12), with the simplification that currents in all three phases are equal. The power incoming at the secondary substation $P_{\text{in}}$ is calculated as the sum of the total load from all apartments and all feeder and transformer losses. The total grid loss fraction is defined as in equation 3.15.

3.3 Estimation of economic incentives

The introduction of smart grid principles into the distribution grid and the increasing of system efficiency require significant investments from the distribution system operators. It is important that these DSO’s are rewarded some economical benefit in order to avoid under investing in these area’s. Demand response is one of the area’s that requires investments from the DSO. This section will look into their potential financial gains from rolling out a demand response programme.
The goal of the DSO, as with any company, is to make profit. The profit of the DSO is given by the basic equation

\[ \text{DSO Profit} = \text{DSO Revenue} - \text{DSO Costs}. \]  

(3.25)

The roll-out of demand response can affect both revenue and costs. Introducing DR involves a change in the DSO’s tariff structure, the average price that consumers pay may change, altering the revenue. Although this has not been considered in this thesis, a demand response program could also lower the total consumption level by peak shaving, with a detrimental effect on the DSO’s income. Generally, these changes in revenue are difficult to model. The focus here will therefore be on the cost side of the equation. There are three main costs that could be affected by demand response [19]:

- Cost of losses: by distributing the load more evenly over time, demand response can help to reduce power losses in the grid. Since the DSO is responsible for the procurement of grid losses in Sweden, reducing them represents an important opportunity for considerable cost reduction [10]. The losses can be purchased in different ways, either via long-term fixed price contracts or on the market. In this analysis, it will be assumed that all losses are purchased at market price. In that case, shifting load towards off-peak hours can also have a secondary effect on the cost of grid losses. Losses appearing at off-peak hours can usually be purchased at a lower price, especially when losses are diverted to night hours [12].

- Cost of fee paid to feeding grid: Swedish DSOs pay a ‘feeding-grid’ charge to the high voltage transmission operator in order to receive power [19]. This charge is made up of three different parts: a yearly fixed fee, a variable charge based on the amount of energy transferred (SEK/kWh) and a third part based on the maximum power that is drawn from the HV-grid by the distribution grid (SEK/kW). The first two parts are not affected by demand response, since the fixed fee is paid ex-ante and only load shifting is considered in this thesis so that the energy based fee will be unaltered. If DR manages to reduce the peak load of the grid, the power-based part of the fee could be reduced.

- Postponing grid investments: DSOs need to invest in their grid capacity in order to accommodate its peak loads. Due to increasing electrification (e.g. rise in number of electric vehicles), the peak power demand is expected to grow in the near future. Demand response could help to mitigate this increase in peak load, and reduce or at least postpone the capital costs that are needed to expand the grid. It can also be argued that reducing load variations and better utilization of grid equipment will lead to an increase in their life span [19].

The first two costs are operational costs (OPEX), while the third one is related to investment costs (CAPEX). The CAPEX part will not be quantitatively analysed here. As was discussed in section 2.3, the OPEX are divided in controllable and non-controllable costs by the regulator. The non-controllable costs are passed through to the customer entirely, and have no influence on the profit of the DSO. With the start of a new regulatory period in 2016, the cost of power losses and the feeding grid charge have been changed from completely non-controllable to partly controllable costs. The share of costs that is burdened by the DSO is fixed at 50% for power losses
(see equation 2.9), while for the feeding grid cost it will be determined by the average load factor (see equation 2.10).

The potential cost reductions and the division over DSO and consumers will be calculated for the period of 01-01-2017 to 22-03-2017, for which load profile data are available. The results will also be scaled up to a full regulatory period of three years.
Chapter 4

Results and discussion

4.1 Evaluation of the demand response pilot in SRS

4.1.1 Impact on building level

First, the impact of the DR will be analysed at an aggregated level. The 154 ‘smart’ apartments that participate in the DR are spread over three different buildings, that are fed by three different feeders. It is therefore important to analyse the load impact on the scale of these buildings, to later make the link to the losses in their respective feeders.

Both the daily load factor $LF_d$ and daily load shift $LS_d$ are calculated for the total SRS load, and the aggregated load of the three buildings (Alpha, Beta and Gamma) individually. The daily load shift for the total SRS load and the different buildings separately over the analysed period (from 01/01/2017 to 22/03/2017) is shown in Figure 4.1. There are a few first conclusions that can be made from these figures. First of all, there appears to be a high volatility of the daily load shift, as there is a strong variation of the load shift from day to day. Secondly, it can be seen that the load shift of the total apartment group is mostly lying between $-5\%$ and $1\%$. The hypothesis of the Stockholm Royal Seaport Urban Smart Grid pre-study that positive load shifts of $5\%$ to $15\%$ are possible seems an overestimation based on this [1]. Finally, these plots also indicate that there might be considerable differences in the impact of the demand response for the different SRS customer groups. The Gamma customers appear to show the best load shift, whereas the Beta customers seem to have the most negative load shift.

Analogous plots were made for the daily load factor in Figure 4.2 and similar trends can be identified as with the load shift. There is also a volatility to the load factor of the SRS customers, that appears higher than for the reference customers. One possible explanation for this is that the reference customer load factor is based on aggregated data of more than 400 consumers, which might lead to more averaged out results compared to the smaller SRS customer groups, that consist of only a few dozens of customers. Considerable differences also appear to exist between the different buildings, with the Gamma building having the best load factor. A statistical summary of these load shift and load factor curves are given in Table 4.1.

Rather than estimating trends in load shifts from Figure 4.1, it’s better to use statistical methods to determine sound estimates of the impact of the demand response. The first thing that has to be checked, is whether the observed daily load shifts are statistically significant, or rather due to random variations. The electric energy demand during a certain hour is a stochastic variable, so that even between very similar customers there will always be variations in load profile, and therefore a
certain load shift. If the consumption behaviour of both customers however is truly the same, these variations will be random and the average load shift over time will be zero. As shown in Table 4.1 however, the average load shifts are not zero for the SRS customers. Based on the 81 day samples presented in Figure 4.1, it is possible to assess if the average daily load shift deviates significantly from zero and to say with a certain confidence how big the average daily load shift really is.

First it will be statistically tested whether the average daily load shift of the SRS customers, \( \mu \), differs significantly from zero, or equivalently whether the average (normalised) peak load consumption of the SRS customers equals that of the reference customers. The test problem is formulated as follows:

Test type: one sample test

Hypothesis:

\[
\begin{align*}
\text{null hypothesis } H_0: & \quad \mu = 0 \\
\text{alternative hypothesis } H_1: & \quad \mu \neq 0
\end{align*}
\]

Significance level: \( \alpha = 5\% \)

The probability distribution of the daily load shift is unknown, but because of the high sample size (n=81) the central limit theorem allows to approximate the distribution of the sample mean as normal. This allows the use of the Student’s t-test to test the hypothesis [5]. The statistic used in this test and its distribution are:

\[
T_n = \frac{\bar{x}}{s_n / \sqrt{n}}
\]

\[
T_n \sim t_{n-1}
\]

Figure 4.1: Daily load shift, calculated as in equation 3.3, for the total SRS load and the SRS load in the three different buildings.
4.1. Evaluation of the demand response pilot in SRS

![Figure 4.2: Daily load factor, calculated as in equation 3.4, for the total SRS load and the SRS load in the three different buildings.](image_url)

, with the \( \bar{x} \) the sample mean, \( s_n \) the sample standard deviation and \( n \) the sample size. \( t_{n-1} \) indicates a t-distribution with \( n - 1 \) degrees of freedom [5]. The test will be done for both the three buildings individually as for the total SRS customer group. For the Gamma building, the days with missing metering data (see Figure 3.3) will be omitted in this test. The same is done for the total load. The results from these t-tests are given in Table 4.2. The expectations that were formulated from the figures before are confirmed. The table shows that the null hypothesis (H\(_0\)) has to be rejected for all customer groups, since all p-values are practically zero. This means that the alternative hypothesis (H\(_1\)) is accepted and the SRS customers thus exhibit a significant load shift compared to the reference customers. This load shift however, is negative, meaning that the SRS customers consume on average more during the peak hours. The only group for whom this is is not true, are the Gamma customers. They show a significant, positive load shift of around 1%. For the total group of smart apartments, the average daily load shift is with 90% certainty between -2.5 and -3.2.

The next step in the impact analysis is to investigate whether the demand response program effectively contributes to the load shifting. In reality, such a causal relationship is difficult to prove. The only thing that can really be observed is correlation. If the demand response works well, it is expected that hours with higher prices should result in load being shifted away from these hours, giving a positive load shift. Because of the way the price signal is designed, the difference in price between the peak and off-peak hours is a lot bigger than the differences between different off-peak and different peak hours (see Figure 2.4d). This means that the daily load factor already answers the correlation question, since it indicates the load shifts at the hours with the high prices. Customers with a negative load shift are
### Table 4.1: Summary of observed values of load shift and load factor for the different buildings and reference consumers.

<table>
<thead>
<tr>
<th>Quantity</th>
<th>Unit</th>
<th>Building</th>
<th>Mean</th>
<th>Q1</th>
<th>Q3</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Load shift [%]</td>
<td></td>
<td>Total</td>
<td>-2.88</td>
<td>-4.04</td>
<td>-1.94</td>
<td>-5.78</td>
<td>1.07</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Gamma</td>
<td>1.17</td>
<td>-0.22</td>
<td>2.56</td>
<td>-6.16</td>
<td>6.89</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Beta</td>
<td>-4.26</td>
<td>-6.25</td>
<td>-1.92</td>
<td>-9.31</td>
<td>1.94</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Alpha</td>
<td>-3.82</td>
<td>-5.32</td>
<td>-2.68</td>
<td>-7.05</td>
<td>-0.22</td>
</tr>
<tr>
<td>Load factor [-]</td>
<td></td>
<td>Total</td>
<td>0.57</td>
<td>0.53</td>
<td>0.59</td>
<td>0.49</td>
<td>0.68</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Gamma</td>
<td>0.61</td>
<td>0.56</td>
<td>0.66</td>
<td>0.41</td>
<td>0.84</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Beta</td>
<td>0.50</td>
<td>0.46</td>
<td>0.54</td>
<td>0.39</td>
<td>0.63</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Alpha</td>
<td>0.58</td>
<td>0.54</td>
<td>0.60</td>
<td>0.47</td>
<td>0.76</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Reference</td>
<td>0.62</td>
<td>0.60</td>
<td>0.64</td>
<td>0.58</td>
<td>0.71</td>
</tr>
</tbody>
</table>

### Table 4.2: Results from t-tests for average load shift and Spearman correlation test between load shift and price signal of the different customer groups.

<table>
<thead>
<tr>
<th></th>
<th>Total</th>
<th>Beta</th>
<th>Alpha</th>
<th>Gamma</th>
</tr>
</thead>
<tbody>
<tr>
<td>n</td>
<td>64</td>
<td>81</td>
<td>81</td>
<td>64</td>
</tr>
<tr>
<td>t</td>
<td>-14.6</td>
<td>-14</td>
<td>-21</td>
<td>4.19</td>
</tr>
<tr>
<td>p</td>
<td>≈ 0</td>
<td>≈ 0</td>
<td>≈ 0</td>
<td>≈ 0</td>
</tr>
<tr>
<td>$\mu_{90%}$</td>
<td>[-3.2;-2.5]</td>
<td>[-4.7;-3.7]</td>
<td>[-3.5;-4.1]</td>
<td>[0.7;1.4]</td>
</tr>
<tr>
<td>$\rho$</td>
<td>-0.30</td>
<td>-0.49</td>
<td>-0.056</td>
<td>0.018</td>
</tr>
<tr>
<td>p</td>
<td>≈ 0</td>
<td>≈ 0</td>
<td>0.027</td>
<td>0.46</td>
</tr>
</tbody>
</table>

- n = sample size
- t = sample statistic
- $p = p$-value
- $\mu_{90\%} = 90\%$ confidence interval for the real average load shift
- $\rho = $ Spearman correlation coefficient
4.1. Evaluation of the demand response pilot in SRS

Therefore expected to automatically show a negative correlation with the price signal and vice versa. Table 4.2 gives the Spearman rank correlation coefficient for the load shift of the SRS customers with the price signal. The Spearman correlation captures any monotone relationship between two variables, as opposed to the Pearson correlation coefficient which represents only linear relationships [5]. The basic premise of the Pearson and Spearman correlation is illustrated in Figure 4.3. More detailed discussion on this topic can be found in most basic statistic textbooks.

The p-value of a Spearman correlation test is also provided. The null hypothesis of this test says that the correlation between the two variables does not significantly differ from zero. It can be concluded that the total load shift shows a significant negative correlation with the price signal, mainly because of the Beta customers. For the total SRS load, a plot of the hourly load shift versus the value of the price signal is given in Figure 4.4. The negative correlation means that hours with higher prices generally result in higher consumption by the SRS customers. It goes without saying that this is merely a correlation and no causality effect. More interesting is the insignificant correlation of the load shift and price signal for the Gamma customers. Although these consumers had a positive average load shift, there seems to be no clear link with the price signal. In conclusion, correlation analysis suggests that the influence of DR on the observed load shift is small and that there could be external factors that mainly explain the size of the load shift. The results from Table 4.1 indicate a difference in the average load shift between the different buildings. Especially the Gamma building, which is the only one with a positive average load shift. This can be partly due to the lower amount of Gamma customers compared to the other two groups, as it could be a coincidence that customers with an inherently lower peak consumption are in the Gamma building. On the other hand, it should be noted that the different apartments differ in regard to their energy consumption level, which was not captured yet since only normalised load was used.

\[
\begin{align*}
\text{Pearson: } & 0.06 \\
\text{Spearman: } & 0.05 \\
\text{Pearson: } & 0.98 \\
\text{Spearman: } & 1.00 \\
\text{Pearson: } & 0.90 \\
\text{Spearman: } & 1.00 \\
\text{Pearson: } & 0.01 \\
\text{Spearman: } & 0.00
\end{align*}
\]

Figure 4.3: Illustration of how the Pearson and Spearman correlation coefficients represent certain relations between two variables.
The average daily electricity consumption of the observed Walin apartments equals around 17 kWh per day, whereas it is only around 8 kWh for the Alpha and Beta apartments. It was already suggested from literature in subsection 2.2.4 that different types of households show different reactions to demand response. It would be interesting in future research to look into other possible factors that can explain the relatively high load shift of the Gamma apartments, such as lifestyle, household size and income level etc.

**Figure 4.4:** Hourly load shift of the total SRS load versus the value of the price signal
4.1.2 Impact on customer level

Some indicators of consumption behaviour were calculated for all individual apartments over the period of 01/01/2017 to 22/03/2017 including average load shift, average load factor, average daily peak load (normalised), average daily total peak hour consumption (see equation 3.2), average daily energy consumption and the average electricity price paid by those consumers. The average electricity price for a customer was calculated as the total cost of electricity over the analysed period (obtained using price signal and individual consumption data) divided by total consumption in this period, or in formula:

$$ \text{Average electricity price} = \frac{\sum_{h} (\text{Price signal}(h) \cdot \text{Consumption}(h))}{\sum_{h} \text{Consumption}(h)} $$

(4.1)

, where $h$ is varied from 01-01-2017 00:00 to 22-03-2017 23:00. The results are summarized in Table 4.3. As was explained in the methodology chapter, clustering of the customers will now be performed on the (normalised) average load shift, average load factor and mode of the peak time using a k-means algorithm.

<table>
<thead>
<tr>
<th>Quantity</th>
<th>Unit</th>
<th>Mean</th>
<th>Q1</th>
<th>Q3</th>
<th>Min</th>
<th>Max</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average load shift</td>
<td>[%]</td>
<td>-3.2</td>
<td>-6.3</td>
<td>0.2</td>
<td>-16.2</td>
<td>7.4</td>
<td>0</td>
</tr>
<tr>
<td>Average load factor</td>
<td>[-]</td>
<td>0.37</td>
<td>0.29</td>
<td>0.43</td>
<td>0.19</td>
<td>0.91</td>
<td>0.62</td>
</tr>
<tr>
<td>Peak time</td>
<td>[-]</td>
<td>18.00*</td>
<td>16.00</td>
<td>19.00</td>
<td>05.00</td>
<td>22.00</td>
<td>18.00</td>
</tr>
<tr>
<td>Peak load</td>
<td>[%]</td>
<td>14.2</td>
<td>11.5</td>
<td>16.9</td>
<td>4.7</td>
<td>24.7</td>
<td>6.7</td>
</tr>
<tr>
<td>Peak consumption</td>
<td>[%]</td>
<td>39.5</td>
<td>36.1</td>
<td>42.5</td>
<td>29.0</td>
<td>52.5</td>
<td>36.2</td>
</tr>
<tr>
<td>Daily consumption</td>
<td>[kWh]</td>
<td>8.2</td>
<td>4.7</td>
<td>9.9</td>
<td>1.2</td>
<td>29.2</td>
<td>7.9</td>
</tr>
<tr>
<td>Average price</td>
<td>[öre/kWh]</td>
<td>103.4</td>
<td>101.3</td>
<td>105.8</td>
<td>96.25</td>
<td>114.16</td>
<td>102.2</td>
</tr>
</tbody>
</table>

* Median was calculated instead of mean

One of the weaknesses of the k means algorithm is that it does not allow to determine the number of clusters needed to represent the data set. It is up to the user to specify the number of clusters. In this case, the number of clusters was varied and chosen so that a big enough range of different customer types was identifiable with still sufficient variation between clusters and a significant amount of apartments per cluster. The number of clusters in the dataset was then settled at eight. The result of the clustering is given in Table 4.4. Each cluster was given a name to represent the general consumption behaviour of its members. For each cluster, the size is given along with the three coordinates (load shift, load factor and peak time) of the centers. These are essentially the average values of the apartments in the cluster. The table also includes the distribution of the Beta, Alpha and Gamma consumers across these clusters. The different clustered load patterns are also visualized in Figure 4.5. These patterns were obtained by summing the load profiles of all members of the cluster, normalising the resulting load in the usual way and taking a one day sample from it.
<table>
<thead>
<tr>
<th>Cluster name</th>
<th>Size</th>
<th>Load shift</th>
<th>Load</th>
<th>Peak time</th>
<th>Peak load</th>
<th>Peak consumption</th>
<th>Average price</th>
<th>Alpha</th>
<th>Beta</th>
<th>Gamma</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>3</td>
<td>126</td>
<td>07:00</td>
<td>0</td>
<td>0.27</td>
<td>10</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>3</td>
<td>85</td>
<td>12:00</td>
<td>0</td>
<td>0.27</td>
<td>10</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>4</td>
<td>121</td>
<td>19:00</td>
<td>1</td>
<td>0.27</td>
<td>10</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>3</td>
<td>1</td>
<td>100</td>
<td>07:00</td>
<td>1</td>
<td>0.27</td>
<td>10</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>4</td>
<td>0</td>
<td>100</td>
<td>19:00</td>
<td>1</td>
<td>0.27</td>
<td>10</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>5</td>
<td>2</td>
<td>100</td>
<td>12:00</td>
<td>1</td>
<td>0.27</td>
<td>10</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>6</td>
<td>3</td>
<td>100</td>
<td>19:00</td>
<td>1</td>
<td>0.27</td>
<td>10</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>7</td>
<td>4</td>
<td>100</td>
<td>12:00</td>
<td>1</td>
<td>0.27</td>
<td>10</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>8</td>
<td>0</td>
<td>100</td>
<td>19:00</td>
<td>1</td>
<td>0.27</td>
<td>10</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>9</td>
<td>2</td>
<td>100</td>
<td>12:00</td>
<td>1</td>
<td>0.27</td>
<td>10</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4.4: Summary of the results from the clustering of consumption data.
4.1. Evaluation of the demand response pilot in SRS

![Graphs showing different load patterns](image_url)

**Figure 4.5:** Visual representation of the eight identified clusters.
Some key takeaways from the clustering results are discussed below:

- The reference customer load profile was also included as a data point. The cluster in which it was classified is named reference in the table. The customers in this cluster behave relatively similar as the reference customers.

- Five of the eight clusters exhibit a negative mean load shift. They are indicated as peak clusters. They can be divided further in customers with a peak in the evening or a peak in the morning, and in small, moderate or severe peaks.

- Two clusters have a significantly higher positive load shift than the reference cluster. One of these two groups has a remarkably higher load factor than any other cluster. It is therefore named the high load factor cluster. The other one has a higher peak load than the reference cluster, resulting in a lower load factor. Since the peak is situated around noon, this still leads to a positive load shift. This cluster is named the active consumer cluster.

- The Alpha and Beta buildings, which were concluded to have a negative load shift in the previous subsection, still contain some active consumer and high load factor members. The Beta building even contains the highest absolute number of consumers from these clusters. However, they are ’masked’ by the high number of peak consumers in these buildings.

- It has to be considered a possibility that some of the high load factor apartments are actually not really inhabited yet and are therefore only running some base load appliances. One of these apartments has an average daily energy consumption of just over 1 kWh. However, the average daily consumption of this total cluster is not remarkably low compared to the other clusters.

One element of the customer level analysis that deserves some extra attention, is the average price paid by the customers for this electricity. The value proposition of demand response programs for consumers usually comes down to reducing the electricity bill. It can be interesting to check how big the potential savings can be. Figure 4.6 gives a plot of the average electricity prices (see equation 4.1) paid by all SRS customers versus their average daily load shift.

![Figure 4.6: Average electricity price paid by SRS consumers as a function of their average daily load shift.](image)

It shows a clear downward trend of the average price with average load shift, but with a rather big spread around this trend. This is confirmed by a linear correlation coefficient of -0.72, indicating a clear linear downward trend. However, the
relatively big spread around the linear trend is seen most remarkably by the fact that the customer with the lowest average price has a negligible load shift. The red line in Figure 4.6 shows a linear fit model of the average price as a function of the load shift, that was calculated using the least squares method. The determination coefficient $R^2$ of this model equals 0.51, indicating that around 50% of the variation in average price is predicted by the model. The model equation is given by:

$$\text{Average price} = 102.2 - 0.52 \cdot \text{LS},$$

(4.2)

where the average price is expressed again in öre/kWh and the load shift LS in percentage. This means that a load shift of 2% will result in a decrease of the electricity cost of around 1 öre/kWh equalling around 1% of the average price. The model can now be used to make a simple estimation of the potential cost savings for the customers in the DR program. The savings will be calculated against a baseline where their consumption pattern is exactly that of the reference customers whilst being subjected to the DR price signal. The average electricity price calculated with equation 4.1 for the reference customer’s load profile equals 102.2 öre/kWh. Using the linear model from equation 4.2, a confidence interval for the expected mean of the average price distribution for a certain load shift can be calculated. For example, for a load shift of 5%, the expected value of the average electricity price will be with 90% certainty between 100.28 and 98.98 öre/kWh.

The percentage of cost savings for an SRS customer compared to reference consumption can be defined as:

$$\text{Cost savings} = 100\% \cdot \left( \frac{C_{\text{REF}} - C_{\text{SRS}}}{C_{\text{REF}}} \right),$$

(4.3)

where $C_{\text{REF}}$ is the total electricity cost of an SRS consumer if their consumption pattern were that of the reference customer (no load shift) and $C_{\text{SRS}}$ the total electricity cost for their actual consumption behaviour. Since the consumed quantity between the reference and actual consumption is assumed to be the same, this expression can be rewritten in terms of the average prices $P_{\text{REF}}$ and $P_{\text{SRS}}$:

$$\text{Cost savings} = 100\% \cdot \left( \frac{P_{\text{REF}} - P_{\text{SRS}}}{P_{\text{REF}}} \right) = 100\% \cdot \left( 1 - \frac{P_{\text{SRS}}}{P_{\text{REF}}} \right),$$

(4.4)

with $P_{\text{REF}} = 102.2$ öre/kWh, the average electricity price of the reference consumer. Table 4.5 gives an overview for the expected cost savings for different levels of load shift. The best load shifts achieved in the SRS project are around 7%. Using the results from this table, the total savings on the yearly electricity bill would be between 85 and 130 SEK for this load shift. This is assuming a daily electricity consumption of 8.2 kWh (the average of the SRS consumers) and a year of 365 days. It should be noted that there are no observations of load shifts higher than around 7%, so the extrapolated estimations for higher load shifts should be used with care.
TABLE 4.5: 90% confidence interval of the expected cost savings achieved with different load shifts for SRS customers.

<table>
<thead>
<tr>
<th>Load shift [%]</th>
<th>Interval [%]</th>
<th>Interval* [SEK]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.1 - 0.9</td>
<td>3 - 28</td>
</tr>
<tr>
<td>2</td>
<td>0.5 - 1.5</td>
<td>15 - 46</td>
</tr>
<tr>
<td>5</td>
<td>1.9 - 3.2</td>
<td>58 - 98</td>
</tr>
<tr>
<td>7</td>
<td>2.8 - 4.3</td>
<td>86 - 132</td>
</tr>
<tr>
<td>10</td>
<td>4.1 - 6.0</td>
<td>126 - 184</td>
</tr>
<tr>
<td>15</td>
<td>6.3 - 8.8</td>
<td>193 - 270</td>
</tr>
</tbody>
</table>

* For a household with a consumption of 3000 kWh per year.

4.2 Grid losses in the SRS grid

An objective of this thesis is to evaluate the loss reduction in the Stockholm Royal Seaport grid due to demand response. The first step for this is to calculate the actual losses in the grid. In this section, measurement data from the SRS smart grid will be used to evaluated the grid losses in the network using the loss model presented in the previous section.

A first important question is the period of the available data to be analysed. As was already mentioned, the tenants of the smart apartments in this project started moving in from the beginning of January. This creates a period of transition during which the owners gradually start moving into their apartments. It is uncertain how long this moving process will take and after what amount of time the consumption of the households will reach a steady state. A possible way to evaluate whether this transient period has been completed, is by checking the evolution of the transformer and feeder load over time. The daily energy that was distributed via the substations and the two feeders to the smart apartments are plotted in Figure 4.7. Some periods are left out in these figure since there was no data available on those days. It can be seen that at substation level, there are considerable changes in the daily load level. Contrary to what would be expected in the transition from winter to spring, the daily load is growing. A possible explanation could be people moving in to the new apartments or new businesses opening in the neighbourhood. The load for feeders to the smart apartments seems to be more stable, with a slight, expected decrease towards April and May. From these figures, there seems to be no evidence of a transition period with increasing load from households moving in. Because of the load changes over time, it will be interesting to compute the grid losses for example on a monthly basis rather than for one whole period. Note that no measurements for the feeder to the Gamma apartments were available at the time of writing this thesis yet. This feeder will therefore be excluded from the analysis in this section.

The loss fractions for the two substations and ‘smart’ feeders will now be calculated from January to May, on a monthly basis. Loss fractions will be referred to with Nf, as is done in the regulation (cfr. equation 2.9). Recall that the loss fractions are calculated for the feeders, the transformer and total grid as in equations 3.9, 3.14 and 3.15 respectively. All quarterly power measurements were converted to energy
4.2. Grid losses in the SRS grid

![Graphs showing grid losses over time for different substations and feeders.](image)

(A) Substation Jaktgatan

(B) Substation Bobergsgatan

(C) Feeder Alpha apartments

(D) Feeder Beta apartments

**Figure 4.7:** Evolution over time of the total daily energy distributed over the two analysed substations and ‘smart’ feeders.

![Graphs showing percentage losses over time for different substations.](image)

(A) Jaktgatan

(B) Bobergsgatan

**Figure 4.8:** Evolution over time of the total loss fraction of the two analysed substations.
values by multiplying with 900 seconds. The loss fractions were then obtained by summing all energy loss values over the analysed period and dividing by the sum of all transformer or line energy values. For the calculation of the total loss fraction, the length of all feeders was assumed to be equal to one kilometer. The results are given in Table 4.6. The evolution of the daily loss fraction over the full analysed period can be seen in Figure 4.8.

A first trend that can be seen in this table is that loss fractions in general are decreasing over time. The effect looks more outspoken for the transformer losses than for the feeders. The total loss fraction for the Jaktgatan 39 substation seems to be relatively stable, at about 3.2%. Feeder losses are reported for all measured feeders in Figure 4.9. This plots surprisingly indicate that the feeders to the demand response apartments (feeder 21 for Jaktgatan and feeder 10 for Bobergsgatan) show higher loss fractions than the other feeders, whereas DR was expected to reduce losses. However, it should be noted that it is hard to compare loss fractions for different feeders, because of differences in load level, power factor etc. between feeders. The feeders supplying the smart apartments generally exhibit higher loads than the other feeders. As was mentioned several times by now line losses scale quadratically with the line load, and because loss fraction equals line losses divided by line load, it is expected that the loss fraction increases with the line load. It’s also worth mentioning that the Bobergsgatan substation usually has a lower power factor than the Jaktgatan one. The average power factor of the Jaktgatan substation is around 0.95 while the Bobergsgatan one averages only 0.85. This causes the loss fraction in the Bobergsgatan feeders and transformer to be higher. A last important note is that the Beta and Alpha apartments (which are fed by Bobergsgatan feeder 10 and Jaktgatan feeder 21 respectively) did not show a load shift away from peak hours compared to the reference customers. Assuming that consumers on other feeders behave like the reference customers, it should not surprise that the smart apartment feeders do not show lower loss levels.

The loss fractions in the overall Bobergsgatan 61 grid are significantly higher. There are different possible explanations for this. The first reason has to do with the no-load losses in the transformer. Both substations contain the same type of transformer, with the same level of no-load losses. As can be seen in Figure 4.7a and Figure 4.7b,
### Table 4.6: Overview of loss fraction of transformers, smart feeders and total grid for the two analysed substations.

<table>
<thead>
<tr>
<th>Period</th>
<th>Jaktgatan 39</th>
<th>Bobergsgatan 61</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Feeder 21</td>
<td>Transformer</td>
</tr>
<tr>
<td>Unit:</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[%/km]</td>
<td>[%]</td>
</tr>
<tr>
<td>January</td>
<td>2.73</td>
<td>1.38</td>
</tr>
<tr>
<td>February</td>
<td>2.82</td>
<td>1.35</td>
</tr>
<tr>
<td>March</td>
<td>2.74</td>
<td>1.27</td>
</tr>
<tr>
<td>April</td>
<td>2.50</td>
<td>1.24</td>
</tr>
<tr>
<td>May</td>
<td>2.50</td>
<td>1.24</td>
</tr>
<tr>
<td>Total</td>
<td>2.66</td>
<td>1.29</td>
</tr>
</tbody>
</table>

the daily load of the Jaktgatan substation is more than twice the load of the Bobergsgatan substation. Since the no-load losses don’t scale with the transformer load, the level of no-load losses is the same for a lower load, resulting in a higher loss percentage for the Bobergsgatan substation. It should be noted however, that for the Bobergsgatan substation, feeder 22’s current measurements indicate zero ampere while it is known to be active. This data error could also be happening to other feeders, leading to the results from Table 4.6 being an underestimation of the real loss levels. Other deviations in the loss level could be because of differences in power factor or load factor between the two substations.

The data that is available from the SRS smart grid can also be used to validate the model for the transformer losses that was proposed in the beginning of this part. The transformer losses can be validated easily. The load and no-load losses can be calculated as was proposed in equations 3.12, 3.11 and 3.10. The sum of these modelled losses can then be compared with the real losses observed in the previous section. These ‘real’ values were obtained as the active power measured at the primary side, minus the active power measured at the secondary side of the transformer. Figure 4.10 shows the accuracy of the model, defined as $100\% \cdot \left( \frac{P_{\text{model}}}{P_{\text{observed}}} \right)$. The plots indicate that, for the Jaktgatan substation, the modelled losses account for only 60% to 70% of the observed losses. For the Bobergsgatan substation the percentage is higher, at about 85% up to almost 100%. There could be different explanations behind this deviation. One cause could be that values of e.g. winding resistances or no-load losses in reality deviate from their reported values. Another reason could be inaccuracy of the smart grid measurement data. The most obvious explanation however, is that the values of the winding resistances increase with the load. The values reported in the transformer’s data sheet are measured with the windings at room temperature. But, when the transformer is in operation, the temperature of the windings significantly increases above room temperature. When comparing Figure 4.7 and Figure 4.10, it can be seen that the model’s inaccuracy is the highest at the moments of highest transformer load. This indicates that warming up of the windings could indeed be a large part of the explanation. However, the model is mainly intended to calculate reductions in loss levels rather than obtaining accurate absolute values. Therefore, this inaccuracy should not pose big problems.
Chapter 4. Results and discussion

4.3 Influence of DR on grid losses

This section will combine the two previous chapters on DR evaluation and network loss calculation, in order to evaluate the effect of demand response on the loss level. To begin, this analysis will be done for the specific SRS network, with the data collected from the smart grid. To be able to get a broader view of the influence of different factors on the success of a DR program to reduce losses, that subsection will be followed by simulation results from a fictitious grid configuration.

4.3.1 SRS Case analysis

This subsection will try to link up the results from the ex-post analysis of both load shift and loss fraction that was done for the Stockholm Royal Seaport grid in the previous two sections. The ideal outcome of this section is to get an estimation of the expected loss reductions for a certain amount of load shift. A plot of the building’s daily load shift versus the daily loss fraction in its feeder is given, for both the Beta and Alpha building, in Figure 4.11 and 4.12 respectively. As was mentioned in section 3.2.2, there is no data available from the Gamma building’s feeder. The analysis will therefore be limited to the Alpha and Beta buildings.

It appears from these figures that there exists no correlation between the load shift and level of losses in the feeders. Calculating the Spearman correlation between daily load shift and loss factor confirms the impressions from the figures. As mentioned before, the Spearman correlation coefficient reflects monotone relationships of any kind between two variables (see Figure 4.3). The values of the correlation for both feeders is given in Table 4.7. For the Alpha building, there is a positive correlation observed, meaning that higher load shifts result in more losses. For the Beta building the observed correlation is positive, as expected, but both observed correlations are statistically insignificant as indicated by the high p-values of the Spearman correlation tests performed on these samples. It can therefore not be concluded that there exists a dependence of network losses on the load shift in the SRS grid. There are many possible explanations for this unexpected result.

Part of the reason is probably that the smart apartments in these two buildings make up only part of the total number of apartments. This would diminish the influence of the load shift on the load profile for the feeder. To check this, the aggregated
4.3. Influence of DR on grid losses

![Graph](image1)

(A) Real value

(B) Normalised so that $N_{f_{\text{max}}} = 1$

**Figure 4.11:** Plot of the Alpha customer’s daily load shift versus the daily loss fraction in its feeder (substation Jaktgatan feeder 21).

![Graph](image2)

(A) Real value

(B) Normalised so that $N_{f_{\text{max}}} = 1$

**Figure 4.12:** Plot of the Beta customer’s daily load shift versus the daily loss fraction in its feeder (substation Bobergsgatan feeder 10).

**Table 4.7:** Spearman correlation observed between daily load shift of Alpha and Beta building and the daily loss fraction in their feeders.

<table>
<thead>
<tr>
<th></th>
<th>Alpha</th>
<th>Beta</th>
</tr>
</thead>
<tbody>
<tr>
<td>n</td>
<td>67</td>
<td>16</td>
</tr>
<tr>
<td>$\rho$</td>
<td>0.11</td>
<td>-0.25</td>
</tr>
<tr>
<td>$p$</td>
<td>0.37</td>
<td>0.36</td>
</tr>
</tbody>
</table>

$n =$ number of days observed

$\rho =$ Spearman rank correlation observed

$p =$ p-value of Spearman correlation test
daily smart apartment metering for each building was divided by the total feeder load for that day (see section 3.2.2 for calculation method). The results are given in Figure 4.13. It should give an estimate of what percentage of the total number of apartments in a building are participating in the DR. The smart apartments make up between 60 and 80% of the Alpha building, for the Beta building this is between 50 and 60%. For more than half of the total load, the load shift would be expected to have a visible impact on the feeder losses.

![Figure 4.13: Percentage of daily load to feeder accounted for by the smart apartments’ consumption.](image)

The calculations so far in this section did not allow to find a clear link between the load shift of the smart apartments on one hand, and the network losses in the SRS network. It was not clear whether this was due to external factors influencing the loss level, a too small number of smart apartments, errors in the data collection and processing or some other reasons. The rest of the section will utilise the simulation model proposed in 3.2.3, that can simulate the grid operation when subjected to a certain consumer load. By not varying any grid conditions except for the smart apartments’ load shift, it is expected that the real influence of DR on the losses can be found. The simulations will be done by increasing the share of smart apartments in the building to 100% using the \( f_{SRS} \) parameter from the model, for a grid with one feeder \( (N_F = 1) \). The normalised load profile for the period 01-01-2017 to 22-03-2017 of both the reference customers and the Alpha customers was used as input for the model. The model parameters were chosen in order to represent the situation of the Alpha feeders as realistically as possible. \( E_d \) was set as the average daily load of the Alpha consumers (7 kWh) and the power factor PF as the average of the Jaktgatan substation (0.95). The total number of apartments \( N_C \) was chosen rather arbitrarily as 100, which results in a total building load that is similar to the building that contains the Alpha apartments in reality. The simulation was then executed for \( f_{SRS} = 1 \), meaning that all customers in the building are subject to demand response. The resulting daily line loss fraction is plotted as function of the daily load shift in Figure 4.14. It seems reasonable to approximate the relation between load shift and feeder losses as linear. This feeling is confirmed by a Pearson correlation coefficient of -0.72 and Pearson correlation test p-value of the order \( 10^{-14} \). A linear fit model can be computed with the least squares method. The resulting equation is:

\[
N_{f_{line}} = 2.7 - 0.03 \cdot LS, \tag{4.5}
\]

with \( LS \) and \( N_{f_{line}} \) both in percentage. This means that a 1% load shift by the Alpha customers is expected to result in a line loss reduction of 0.03 percentage
4.3. Influence of DR on grid losses

points. On a loss level of around 3% this comes down to a reduction of roughly 1% per one percent of load shift. The same process was repeated for the load profile of Gamma and Beta. The average daily consumption for Beta and Gamma apartments was 7 and 17 kWh respectively. The load factor for their substation averaged 0.85. The total number of apartments was set at 100 with $f_{SRS} = 1$ again. The results are not visualised, but the linear models for the three buildings are summarized in Table 4.8. The table also includes the p-value of an F-test and the determination coefficient of the model. The null hypothesis of the F-test says that the calculated coefficient $\beta_1$ does not deviate significantly from zero, indicating that the model has no use to predict loss levels. Since the p-value is extremely small (<0.001) for all buildings, the models can be accepted as significant. The determination coefficient then gives an indication of how much of the variation in losses is explained by the load shift. The $R^2$ value of the Alpha building is a lot higher than for the other buildings, resulting in better predictions of the loss level for a certain load shift using their linear models. As reported in Table 4.1, the Alpha and Beta building currently have a negative load shift compared to the reference customers. Their respective linear models can be used to make an estimate of how the losses would be reduced if these customers were to start reducing their peak consumption and so improved their load shift. The Gamma customers’ load shift shows that achieving significant positive load shifts is possible. For them, possible loss reductions will be calculated if they were to shift some more load away from peak times. For each building, a realistic target for average load shift was set based on the observed daily load shifts. The results for the expected loss reductions are given in Table 4.9.
Chapter 4. Results and discussion

Table 4.8: Summary of the linear regression models for line loss fraction as a function of load shift of the three SRS buildings.

\[ \text{Nf}_{\text{line}} = \beta_0 + \beta_1 \cdot \text{LS} \]

<table>
<thead>
<tr>
<th>Alpha</th>
<th>Beta</th>
<th>Gamma</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta_0 )</td>
<td>2.7</td>
<td>3.7</td>
</tr>
<tr>
<td>( \beta_1 )</td>
<td>-0.03</td>
<td>-0.02</td>
</tr>
<tr>
<td>( p )</td>
<td>( \approx 0 )</td>
<td>( \approx 0 )</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.53</td>
<td>0.20</td>
</tr>
</tbody>
</table>

\( p = p \)-value of F-test
\( R^2 = \) Coefficient of determination

Table 4.9: Current feeder losses and potential loss reductions for a targeted load shift, assuming 100% smart apartments in the building.

<table>
<thead>
<tr>
<th>Current average load shift [%]</th>
<th>Alpha</th>
<th>Beta</th>
<th>Gamma</th>
</tr>
</thead>
<tbody>
<tr>
<td>Target average load shift [%]</td>
<td>0</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>Current feeder losses* [%]</td>
<td>2.81 - 2.83</td>
<td>3.81 - 3.86</td>
<td>8.18 - 8.33</td>
</tr>
<tr>
<td>Target feeder losses* [%]</td>
<td>2.67 - 2.72</td>
<td>3.68 - 3.79</td>
<td>7.86 - 8.12</td>
</tr>
<tr>
<td>Loss reduction* [%]</td>
<td>4.0 - 5.2</td>
<td>2.0 - 3.3</td>
<td>2.5 - 3.9</td>
</tr>
</tbody>
</table>

* 90% confidence interval

4.3.2 Scenario analysis

In the previous subsection, simulations were made that represent the actual state of the Royal Seaport grid and of the overall consumer reactions in the different buildings. It can also be interesting to repeat the exercise for other, fictitious circumstances. For this, the load profiles that were synthesized in the clustering analysis (section 4.1.2) will be used to represent different possible consumer reactions, and build various scenarios. A summary of the different load profile clusters was given in Table 4.4, with a sample of the profiles representing these clusters given in Figure 4.5. By using different cluster profiles as the DR and reference load profiles, the influence of the consumers’ reactions on the losses can be studied. The losses will here not only be calculated for one feeder, but for the entire secondary grid, including substation and secondary feeders. The simulation model here will represent a grid with ten secondary feeders feeding 1000 customers, so that \( N_C = 1000 \) and \( N_F = 10 \) in the model parameters. This also implies that each apartment building houses 100 households. The power factor \( PF \) was set at 0.9, the apartments’ average daily consumption \( E_d = 8 \) kWh and the feeder length \( \ell = 1 \) km. The network loss levels, and more specifically the reduction of them, can now be calculated using different load profiles as input for the simulation model. A first scenario represents the case
4.3. Influence of DR on grid losses

![Image](image_url)

**Figure 4.15**: Change in a normalised load profile sample as share of DR consumers in the building shifts from 0 to 100%.

In which all demand response consumers behave like the high load factor cluster. By varying the fraction of DR consumers in the total amount of apartments, the impact of their load shift on the total load can be decreased or increased. As the $f_{SRS}$ is increased from zero to one, the total load profile evolves more to that of the DR customers. This transition is visualized in Figure 4.15 for $f_{SRS} = 0.0, 0.1, 0.2, \ldots, 1.0$. For all these values, the grid loss fraction was calculated. The (normalised) loss fraction is plotted as a function of the penetration of demand response ($f_{SRS}$). It can be seen in Figure 4.16a that, for these particular DR and reference profiles, there exists an optimal value for the share of DR customers, at 70% in this case. Compared to the situation with all reference customers, this results in a loss reduction of just over 3%. The same exercise was repeated with the profile of the active consumer cluster used as the DR load profile. The loss level curve is shown in Figure 4.16b. The conclusion there is that, even though the active consumer profile has a positive load shift (see Table 4.4), increasing the penetration above 10% causes the network losses to increase above the reference value. This is due to the inferior load factor of the active consumers compared to the reference consumers. This shows that a positive load shift compared to the reference load profile is not always beneficial towards losses.

So far, the impact of load shifting on the losses has been small, even for the 'best'
resulting load profiles, or even negative. A possible explanation for this, is that the reference consumers in the SRS grid already perform well with regard to load factor. Therefore, it is not really representative to compare the SRS consumers with these reference customers. To be able to see the full potential of DR, it could be better to simulate what would happen if ‘bad’ consumers (the ‘peak’ cluster profiles) were turned into ‘good’ consumers (active consumer and high load factor profiles). By combining different cluster profiles as reference and DR load profiles, several potential scenarios can be built. For each of these scenarios, a maximum potential loss reduction can be found by varying the share of DR consumers as was done in Figure 4.16. This was done for various different scenarios, which are described in Table 4.10 with the results displayed for eight of them in Figure 4.18. This plot shows the change of the grid loss fraction with $f_{SRS}$ for each scenario, normalised so that $N_f$ is always equal to one for zero percent DR consumers. Figure 4.18 shows that in all but one of these eight highlighted scenarios, there is a reduction in losses with increasing number of DR consumers. The greatest potential is seen in the scenario where the reference customers have a severe morning peak profile, and are converted to high load factor consumers with demand response. These are unsurprisingly the clusters which had the worst and best load factors respectively. The average reduction in losses is estimated at just under 25% for this scenario. The severe evening peak to high load factor scenario shows similar loss reductions.

To put these loss reductions into perspective, it’s interesting to see how much loss reduction can be achieved by increasing the power factor of the grid. The loss reductions in Figure 4.16 were calculated for a power factor of 0.90. Taking the maximum loss reduction of scenario 2 (Figure 4.16a), which was for $f_{SRS} = 0.7$, the power factor can now be varied from 0.9 to 1 in this point. The resulting extra loss reduction is shown in Figure 4.17. The plot shows that losses decrease almost linearly with the power factor (in reality the relation is not linear but of the form $1/x$). An increase of the power factor to 0.95, for example, gives an extra 10% reduction of the loss level.

![Figure 4.17: Reduction of grid loss fraction with improving power factor.](image)
### Table 4.10: Specification of different scenario’s with their optimal DR penetration, optimal loss reduction, average daily load shift and average daily load factor for this optimal point.

<table>
<thead>
<tr>
<th>n°</th>
<th>Reference Profile*</th>
<th>DR Profile*</th>
<th>$f_{opt}$</th>
<th>$N_{f_{opt}} / N_{ref}$</th>
<th>$LS_d$ [%]</th>
<th>$LF_d$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Reference</td>
<td>Active Consumer</td>
<td>0.1</td>
<td>0.999</td>
<td>0.2</td>
<td>0.64</td>
</tr>
<tr>
<td>2</td>
<td>Reference</td>
<td>High Load Factor</td>
<td>0.7</td>
<td>0.967</td>
<td>3.2</td>
<td>0.70</td>
</tr>
<tr>
<td>3</td>
<td>Severe Evening Peak</td>
<td>Moderate Evening Peak</td>
<td>1</td>
<td>0.902</td>
<td>5.1</td>
<td>0.48</td>
</tr>
<tr>
<td>4</td>
<td>Small Evening Peak</td>
<td>Active Consumer</td>
<td>0.9</td>
<td>0.853</td>
<td>12.5</td>
<td>0.54</td>
</tr>
<tr>
<td>5</td>
<td>High Load Factor</td>
<td>Active Consumer</td>
<td>1</td>
<td>0.765</td>
<td>16.3</td>
<td>0.69</td>
</tr>
<tr>
<td>6</td>
<td>Severe Morning Peak</td>
<td>Small Morning Peak</td>
<td>1</td>
<td>0.839</td>
<td>8.9</td>
<td>0.56</td>
</tr>
<tr>
<td>7</td>
<td>Moderate Evening Peak</td>
<td>Active Consumer</td>
<td>0.7</td>
<td>0.819</td>
<td>10.2</td>
<td>0.56</td>
</tr>
<tr>
<td></td>
<td></td>
<td>High Load Factor</td>
<td>0.9</td>
<td>0.755</td>
<td>15.4</td>
<td>0.68</td>
</tr>
<tr>
<td>8</td>
<td>Small Evening Peak</td>
<td>Active Consumer</td>
<td>0.5</td>
<td>0.976</td>
<td>2.6</td>
<td>0.57</td>
</tr>
<tr>
<td></td>
<td></td>
<td>High Load Factor</td>
<td>0.9</td>
<td>0.895</td>
<td>7.0</td>
<td>0.69</td>
</tr>
</tbody>
</table>

*Description of the different profiles is given in Table 4.4 and Figure 4.5.

![Figure 4.18: Evolution of normalised grid losses with DR penetration for each scenario.](image)
4.4 Influence of DR on DSO economy

The results from the scenario analysis can now be used to make estimations of possible cost reduction from implementing demand response. The analysis will only be done for the fictitious scenarios and not for the real SRS case, since the overall load shift was largely negative and no positive cost savings are therefore expected. Savings will first be calculated for the analysed period (1st of January to 22nd of March), and will then be scaled up to one year. For the calculation of loss levels and peak loads, the simulation model from the previous section will be used. The model parameters are chosen in such a way to represent the actual situation of the SRS grid. This involves two secondary substations, each feeding 1000 consumers with an average daily consumption of 8 kWh, via ten outgoing feeders each. This results in a total distributed energy of 648 MWh for the analysed period, or 5,840 MWh per year for the two substations combined. To get an idea of the potential cost reductions for a full scale implementation of DR, the calculations will be repeated for the total distributed energy and number of customers of DSO Ellevio, for which data from 2014 was found online (then: Fortum Distribution) [15]. This information is presented in Table 4.11. The cost reduction from the reduction of grid losses and from reducing the feeding grid charge can now be calculated for the different scenarios presented in Table 4.10, for both the scale of the SRS project and an entire DSO.

<table>
<thead>
<tr>
<th>Table 4.11: Scale of the SRS project compared to the total size of Ellevio’s distribution grid [15].</th>
</tr>
</thead>
<tbody>
<tr>
<td>SRS</td>
</tr>
<tr>
<td>Yearly distributed energy [GWh]</td>
</tr>
<tr>
<td>Number of customers [-]</td>
</tr>
</tbody>
</table>

Cost of grid losses

Recall that the incentive to reduce network losses in the revenue regulation, $K_n$, is given by equation 2.9. The reduction of grid losses is known for each scenario from the previous section (see Table 4.10), and the amount of distributed energy is described above. The only thing left is to determine the cost of losses. For this, it will be assumed that losses are to be purchased from the sport market. With Elspot day-ahead price data from Nordpool, the average cost of losses in the analysed period was determined to be around 300 SEK/MWh [26]. As was mentioned in subsection 2.3.3, most DSO’s had a cost of grid losses between 0.25 and 0.65 kSEK/MWh in 2012. The value of 0.30 kSEK/MWh used here seems therefore reasonable. In a first step, the size of the incentive was calculated for the analysed period only, which includes 81 days (from 01-01-2017 to 22-03-2017). The result was then scaled up uniformly to one full year by multiplying with $\frac{365}{81}$. Finally, the size of the incentive for the complete DSO per year was calculated in the same way. The results are given for eight different scenarios in Table 4.12. Recall that scenario 1 and 2 use reference customers like the ones used as reference in the majority of this thesis, and are therefore the most realistic scenarios for the Stockholm Royal Seaport project. For each scenario, the optimal loss reduction from Table 4.10 was used.


### 4.4. Influence of DR on DSO economy

<table>
<thead>
<tr>
<th>Scenario</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>SRS</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Benefit DSO [kSEK]</td>
<td>0.026</td>
<td>1.2</td>
<td>1.2</td>
<td>1.5</td>
<td>2.4</td>
<td>1.6</td>
<td>2.5</td>
<td>0.2</td>
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<tr>
<td>Benefit per customer [SEK]</td>
<td>0</td>
<td>0.6</td>
<td>2.7</td>
<td>3.3</td>
<td>5.3</td>
<td>3.7</td>
<td>5.7</td>
<td>0</td>
</tr>
<tr>
<td>DSO</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Benefit DSO [MSEK]</td>
<td>0.061</td>
<td>2.9</td>
<td>12.5</td>
<td>15.6</td>
<td>25.0</td>
<td>17.3</td>
<td>26.5</td>
<td>22.6</td>
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<tr>
<td>Benefit per customer [SEK]</td>
<td>0</td>
<td>3</td>
<td>14</td>
<td>17</td>
<td>28</td>
<td>19</td>
<td>29</td>
<td>2</td>
</tr>
</tbody>
</table>

**Table 4.13:** Estimate of yearly benefit from increasing system utilization for both the DSO and consumers.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
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</thead>
<tbody>
<tr>
<td>SRS</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Benefit DSO [kSEK]</td>
<td>0</td>
<td>0</td>
<td>163.5</td>
<td>98.4</td>
<td>161.1</td>
<td>336.1</td>
<td>384.2</td>
<td>5.7</td>
</tr>
<tr>
<td>Benefit per customer [SEK]</td>
<td>0</td>
<td>0</td>
<td>72.5</td>
<td>41.9</td>
<td>36.2</td>
<td>132.0</td>
<td>86.3</td>
<td>2.15</td>
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<tr>
<td>DSO</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Benefit DSO [MSEK]</td>
<td>0</td>
<td>0</td>
<td>85.1</td>
<td>51.2</td>
<td>83.8</td>
<td>175.0</td>
<td>200.0</td>
<td>2.9</td>
</tr>
<tr>
<td>Benefit per customer [SEK]</td>
<td>0</td>
<td>0</td>
<td>83.3</td>
<td>48.1</td>
<td>41.6</td>
<td>151.8</td>
<td>99.2</td>
<td>2.5</td>
</tr>
</tbody>
</table>

**Cost of feeding grid access**

As was mentioned in section 3.3, demand response and load shifts are expected to only affect the capacity charge of the feeding grid charge. In reality, the DSO chooses a certain maximum load, and pays a certain price for this subscribed peak demand plus extra penalty charges when peak demands exceed this subscribed level [19]. For simplicity of the analysis here, only a flat rate per kW of maximum power will be considered without any transgressions of this subscribed level. In literature, a value of 185 SEK/kW was found for the cost of subscribed maximum power [12]. The values for the peak load will be calculated from the total load profile in each scenario’s reference profile and optimal loss reduction profile. The resulting feeding grid charge was between 90 and 214 SEK/MWh. Recall from subsection 2.3.3 that the actual cost for the feeding grid was between 20 SEK/MWh and 180 SEK/MWh for most Swedish DSO’s in 2012. Since the cost found here doesn’t include the fixed yearly charge and the energy based fee yet, the modelled cost might be an overestimation. However, since only differences in costs are used this shouldn’t pose a big problem. The average daily load factors were already calculated in Table 4.10. It should be noted that the peak load observed for some DR profile can be significantly higher compared to its reference profile, even though the DR profile has a far superior average load factor, since the peak load is such a momentarily value. This will result in a zero incentive. Results for the eight scenarios are given in Table 4.13.
Chapter 4. Results and discussion

Table 4.14: Estimate of total yearly benefit for both the DSO and consumers.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
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<tbody>
<tr>
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<td></td>
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<td></td>
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<td>SRS</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Benefit DSO [kSEK]</td>
<td>0.026</td>
<td>1.2</td>
<td>168.8</td>
<td>105.0</td>
<td>171.7</td>
<td>343.5</td>
<td>395.5</td>
<td>6.7</td>
</tr>
<tr>
<td>Benefit per customer [SEK]</td>
<td>0</td>
<td>1</td>
<td>75</td>
<td>45</td>
<td>42</td>
<td>136</td>
<td>92</td>
<td>3</td>
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<tr>
<td>DSO</td>
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<td></td>
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<tr>
<td>Benefit DSO [MSEK]</td>
<td>0.061</td>
<td>2.9</td>
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<td>66.8</td>
<td>108.9</td>
<td>192.2</td>
<td>226.5</td>
<td>5.2</td>
</tr>
<tr>
<td>Benefit per customer [SEK]</td>
<td>0</td>
<td>3</td>
<td>97</td>
<td>65</td>
<td>69</td>
<td>171</td>
<td>128</td>
<td>5</td>
</tr>
</tbody>
</table>

The total value of the benefits are given in Table 4.14. The benefit for the DSO from reducing grid losses in the SRS grid are small. For a grid-wide implementation of DR, the potential gains for the DSO are a bit more significant, especially for scenarios using peak clusters as reference consumers. Some context for the DSO cost savings: between 2004 and 2014, Fortum Distribution spent a total amount of 12.5 billion SEK on network investments such as improving rural networks and the roll-out of smart meters [15]. The benefits for the customers are low, even in the most optimal scenarios (peak to high load factor). For the cost of the feeding grid connection, savings are found to be higher. For scenario 1 and 2 there was no benefit because the DR profile had a higher peak load than the reference profile. This could be due to the fact that both profiles were rather similar for these scenarios, but the DR profiles were aggregated from a smaller amount of consumers and therefore more prone to large variations in load. For the other scenarios, the benefits are a multiple of the loss reduction benefits. One of the scenarios crosses the barrier of 100 SEK in savings per consumer. The average electricity price for domestic consumers, including all taxes and levies, in Sweden was around 1.8 SEK/kWh in 2016 [13]. For a household consuming 3000 kWh per year, this comes down to 5400 SEK per year. Even the best case scenario of 150 SEK cost savings per year represents only a 2% reduction of total electricity cost.

The results are in line with a previous master thesis study at the department of electrical power [12], in the sense that the numbers are in the same order of magnitude and that reducing the feeding grid charge has the most economical impact. However, benefits from this cost reduction are more uncertain, since they are based on the very momentary value of peak demand, and not an aggregated measure like the losses.
Chapter 5

Conclusion

5.1 Evaluation of the demand response pilot project in the Stockholm Royal Seaport project

A pre-study done for the Stockholm Royal Seaport project formulated the hypothesis that the demand response participants would shift between 5 and 15% of their daily electricity consumption from peak to off-peak hours. Based on the observed daily load shifts of the 154 households participating in the pilot project, this hypothesis was found to be rather optimistic. Only a minority of the households had a positive average load shift over the analysed period, meaning that on average they consume less during peak hours than the reference consumers. The highest average daily load shift was, at just over 7%, found to be smaller than the 15% of the pre-study's hypothesis. The biggest negative load shift on the other hand, measured over -16%. The overall load shift was calculated for the three buildings that contain the smart apartments. It was found that the load shift for all three buildings differs significantly from zero. For only one, the Gamma building, the load shift appears to be positive with an observed average daily load shift of 1.17%. The observed average for the Beta and Alpha customers equals -4.26 and -3.82 respectively. This shows that on building level, because of aggregation of different consumer reactions, the 5 to 15% hypothesis is even more optimistic. The strong negative average load shifts of some apartments could indicate that the used method with the reference customer group is not representative for the baseline consumption of (all) the DR consumers. In addition, correlation analysis of the apartments' load shifts and the price signal did not manage to prove a direct link between the two. Analysis of the price paid by the different consumers indicated that the most active consumers (i.e. the ones with the highest positive load shift) are expected to save three to four percent of their annual electricity bill due to their consumption changes, amounting to about 85 to 130 SEK for an average consumer. It is questionable whether these savings give enough incentive to provoke behavioural change for most households. It rather seems to be the case that the variations in load shift are due to inherent differences in the consumers' consumption behaviour. This feeling is strengthened by the strong difference between the average load shift of the Beta and Alpha consumers on one hand, and that of the Gamma apartments on the other hand. It could suggest that certain properties of the Gamma apartments make DR more effective for these households. The idea that demand response is no 'one size fits all' solution was also encountered in literature. One important difference between the different buildings that was found, is the average daily electricity consumption per apartment, which is twice as big for the Gamma apartments compared to the other two buildings. It is important to note that the results of this study are only a temporary evaluation of the demand response program. The span of the analysed data was a rather short period in the beginning of the project, during which the participants
have just moved in and might need some more time to get used to the DR system before they really start shifting loads. The analysed period also consisted of winter months, which might have a detrimental effect on the percentage of daily load shift. This is because during winter, there is a higher base load from lighting so that a smaller percentage of consumption is available for shifting. All these factors might influence the accuracy of the results presented in this thesis, and the validity of its conclusions.

5.2 Impact of demand response on power losses

To calculate loss fractions in a distribution grid, a model was proposed to calculate secondary substation and transformer losses. First, this model was applied to the measurements from the SRS smart grid, to calculate the actual loss levels. The average overall loss fractions of the Jaktgatan and Bobergsgatan substations were 3.23 and 5.21 over the whole analysed period (from January to May), with slightly higher values during winter months compared to the spring months (April and May). The higher losses for the Bobergsgatan substation can be attributed to a lower power factor and lower utilization of the secondary transformer, increasing the share of no-load losses.

Next, the influence of the load shift of DR consumers on the loss fractions was investigated. For the Beta and Alpha buildings, their overall daily load shift was compared to the daily loss fraction of their feeders. There was no correlation found between the two. There could be several reasons for this. First, the share of DR consumers in the total apartment buildings could be too low to make a real impact. This seems unlikely however, especially for the Alpha building since the DR apartments’ consumption accounts for 60 to 80% of the energy distributed over the building’s feeder. A more probable explanation is the strong influence of other factors, such as power factor and load level of the feeder, on the loss fraction. A third cause could be problems with the collection or communication of the grid data.

In order to circumvent these problems, a simulation model was created, based on the loss calculation model proposed earlier. This simulation model was set up to calculate grid losses for certain apartment loads. This allowed to investigate the change of losses with the load shift as only variable and block out the influence of e.g. power factor and total load. With these simulations, a clear influence of the load shift on the feeder losses was found. A linear regression analysis showed that a 1% load shift results in a reduction of feeder losses in the order of 1%.

It was also an objective to see what the influence on the losses would be for different consumer reactions. For this, the simulation model was used with as input the load profiles of the different clusters that were identified in the smart apartment. Different scenarios were tested by combining different clusters as reference and DR consumers. The potential reduction for the SRS reference consumers was found to be limited. An optimal conversion of reference customers in a building into ‘high load factor’ customers resulted in a mere 3.3% reduction of network losses. In other scenarios however, much bigger potential was found. A complete conversion of an entire building of ‘severe peak’ customers into ‘high load factor’ customers resulted in a loss reduction of just under 25%.
5.3 Economic incentives for the DSO and for active consumers

The technical potential of demand response for loss reduction appears to be considerable in grids with strong peak loads. However, in order to be really feasible, sufficient economic incentives for all involved actors are needed. This thesis has looked into possible cost reductions for the DSO and the active consumers.

For the active consumers, a two part cost reduction from demand response is expected. The first part comes from a reduction of the grid operating costs. The benefit from these cost reductions have to be shared between the DSO and the consumers, according to Swedish tariff regulation. For the scenarios that resemble the case of the SRS project, these cost savings are negligible. For the most optimistic scenarios, the estimated cost savings per consumer are in the range of 100 SEK. It’s important that these benefits are spread equally amongst all consumers, independent of their load shift effort. Therefore, it does not provide an incentive for the individual to change their consumption behaviour.

An extra cost reduction can be obtained by active consumers by shifting their consumption to times of low prices. The economic incentive for shifting load away from the defined peak hours was estimated by comparing the average electricity price paid by the SRS consumers and their average daily load shift. The result indicated an expected reduction of about 1 öre/kWh (or 10 SEK/MWh) in average electricity price for every 2% of daily consumption shifted away from peak hours. The best performing consumers (i.e. highest positive load shift) are expected to have a reduction of electricity cost of 2.8 to 4.3 percent. On a yearly basis, for an average sized household (3 MWh yearly consumption), this comes down to 86 to 132 SEK. Combining the most optimistic estimates for both incentives results in a yearly cost saving of around 400 SEK. For an average sized household, this is a reduction of just over 7% of total yearly electricity bill (incl. all taxes and levies). The more realistic scenarios give an almost insignificant cost saving of 20 to 50 SEK per year for the average active consumer. As indicated by the relatively low load-shifts observed in the DR pilot so far, these incentives are probably too small for households to change their consumption behaviour. However, demand response could incite other benefits for the consumer, such as reduced cost of energy production and reduction of greenhouse gas emissions. These benefits were not evaluated in this thesis.

For the DSO, three sources of cost savings were identified: reduced purchasing of power losses, a reduction in fee paid to the feeding grid and a reduction or at least postponing of grid investments. The potential benefits from the OPEX reductions were quantified using the incentives for efficient grid operation implemented by Ei in 2016. The incentive to reduce the system peak load was found to be significantly bigger than the one for reduction of network losses. However, this one is also more uncertain because it is based on the momentarily peak load and not on an aggregated measure such as the overall loss fraction. The total value of the incentives was estimated on a yearly basis, for both the scale of the SRS project (2,000 consumers) and the entire DSO (900,000 consumers). The most optimistic scenarios indicate possible benefits of 300 to 400 kSEK per year for the SRS grid and up to 200 MSEK per year for the entire DSO. These scenarios are however not very realistic for the complete DSO scale since they would require an entire distribution grid of severe peak consumers to be converted to high load factor consumers. The more probable scenarios give a benefit of 1,200 to 6,600 SEK per year for the SRS project and 2.8 to 5.2 MSEK for the entire DSO each year.
5.4 Recommendations

The experience from the research that led to this master thesis contains valuable lessons for the future deployment of demand response. Future research could try and circumvent some of the problems and limitations of this study. The DSO can play an important role in supporting innovative research in the field of demand side flexibility, which will be in its own interest in the long term.

For future research
The technical potential of load shifting to reduce grid losses has been clearly established. Whether consumers will effectively start adapting their consumption behaviour as a reaction to a price signal however seems uncertain from the data analysed in this thesis. It will be interesting to remake the impact analysis presented in this thesis after a longer period of time, for example with one year of measurements available. Several things could be improved in such future research. The first improvement would be to find a better method of defining the reference consumption behaviour for DR consumers. The easiest solution would be to have pre-DR consumption data available for the individual apartments in addition to an external reference group, such as the one used in this thesis. This way, both temporal and selection bias could be eliminated in the data. In reality though, the availability of all this data is very optimistic. The strongly negative load shifts that were found with the reference group method used here, suggest that this is not an optimal way of evaluating load shifts. With individual metering data, different consumer types were identified. It could improve the results to use a separate reference profile for these different types of consumers instead of the same one for all consumers. A second suggestion to future work is to include more information about the different apartments, rather than just consumption data. Other DR literature and the results of this thesis suggest that the reaction of consumers to a price signal varies strongly with the type of household involved. This manifests itself in the SRS project in the higher load shift of the more energy consuming apartments. It’s important to investigate whether this is a coincidence or if there is really a systematic difference. Some factors that can help to predict consumers’ reactions could include household size, education, income level etc. Finally, the estimation of the economic benefits from DR for the DSO is still up for improvement. A more detailed study of the long-term cost reductions (including potential CAPEX savings) combined with information about necessary investments could result in a full cost benefit analysis regarding demand response. The result could be important for utilities to make cost-effective investment decisions. It would also be useful for the regulator in order to evaluate and possibly improve the incentives in the current regulation.

For the distribution system operator
The main takeaway from this report for the DSO is that while the potential gains are considerable, success from implementing demand response cannot be guaranteed. This thesis did not find evidence that the price signal incites a sufficient part of the consumers to change their consumption behaviour to result in a significant shift of load away from peak times. This conclusion seems to be in line with earlier demand response pilots in Sweden. A first recommendation is to take the time to thoroughly evaluate the DR pilot with the participating households, for example through a survey. Their feedback and experiences can help to increase the knowledge of how a
price signal can effectively incite behaviour change. Further research on the topic of consumption flexibility needs to be promoted as well, since it is still a promising way to tackle several major challenges of the electrical power system. It is therefore important that grid operators keep investing in smart grid development, in order to collect reliable grid and consumption data that can be used in future research. The focus for prospective work should be on finding tariff structures or other incentives that effectively manage to make households adapt their consumption behaviour in function of efficient grid operation. Continuous research for working demand response schemes is in the utilities’ best interest in the long term, since it will allow them to fully benefit from the investments made for the smart meter roll-out.
Bibliography


