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Predictive Demand-side Management in District Heating and Cooling Connected Buildings

Thesis submitted in partial fulfilment of the requirements for the degree of Master of Science in Technology.

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Abstract of master's thesis

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Abstract

Contemporary technologies enable the control of energy consumption in buildings in a way which minimizes costs and maximizes consumer comfort. Cost reductions have been seen in District Heating and Cooling systems mostly as energy conservation. On the other hand, consumer comfort is increased by providing steadier indoor temperatures. Lately, literature present has presented a more agile approach of reducing costs by optimizing the consumption of the overall system with Demand-side Management. This approach aims to shift loads from peak load hours without necessarily reducing energy consumption.

This thesis provides a model which applies the thermal capacity of District Heating and Cooling connected buildings as thermal energy storages. An artificial District Heating system with variable production costs was developed for the model in order to form dynamic price signals. These signals were utilized in two simulations. The first optimized existing heat load data from heavy mass buildings to appraise the effect of Demand-side Management, whereas the second modelled the behaviour of individual rooms. Both simulations aimed to store heat beforehand in the building envelope and to discharge it during price peaks. This offered the possibility to consume heating energy based on individual consumption profiles and only take action when the whole system requires it.

The simulation model indicates that predictive Demand-side Management with dynamic price signals reduces heating costs in buildings by 4% during the heating period. The main cost savings occur to energy producers since variable production costs can be decreased by 6% due to load control using 15% of the building stock's heated floor area. The room simulation demonstrated that the building components are able to store heat dynamically by intelligent prediction of occupancy, outside weather, and prices. With an autonomous auction platform, Demand-side Management activities can be targeted to buildings which are most suitable to shift demand. The order of building participation is determined by individual consumer comfort and thermal dissipation.

As predictive Demand-side Management relies on dynamic pricing and engagement of District Heating and Cooling customers and producers, the thesis proposes a concept to achieve a win-win situation for these stakeholders. In order to ensure a reasonable allocation of benefits from Demand-side Management and provide a more accurate demand prediction, new business models could emerge. These models can challenge producers and customers to revalue District Heating and Cooling.

Keywords Demand-side Management, District Heating and Cooling systems, Dynamic Pricing, Prediction, Optimization

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Tiivistelmä

Nykyaikaiset teknologiat mahdollistavat rakennuksen energiankulutuksen hallinnan tavalla, joka minimoi kustannuksia ja maksimoi kuluttajien mukavuutta. Kustannusten alentaminen on kaukolämmössä ja -jäähdytyksessä perinteisesti saavutettu energiansäästöllä. Kuluttajien mukavuutta on taas parannettu tasaisemmalla lämmönjakelulla. Viimeisten vuosien aikana tutkijat ovat esittäneet kysyntäjoustoa ketteränä tapana alentaa systeemitason kustannuksia. Kysyntäjousto pykii siirtämään ajallisesti osan tehon huippukuormista. Energiankulutusta ei välttämättä vähennetä.

Tämä työ tarjoaa mallin, joka hyödyntää kaukolämmitteisten rakennusten lämpökapasiteettia energiavarastoina. Mallia varten on kehitetty kaukolämpöjärjestelmä, jonka antamat hintasignaalit perustuvat muuttuviin tuotantokustannuksiin. Näitä signaaleja hyödynnettiin kahdessa simulaatiossa. Ensimmäinen optimoi kuormia systeemitasolla siirtäen olemassa olevia kulutusprofiileja, kun taas toinen simulaatio käsitteli ihanteellista huonemallia. Molempien simulaatioiden tarkoituksena on varastoida lämpöä etukäteen rakenteisiin ja purkaa sitä hintapiikkien aikana. Toisin kuin aiemmissa tutkimuksissa, lämmönsäätimet reagoivat muuttuviin hintasignaaleihin. Tällä tavalla rakennukset kuluttivat lämmitysenergiaa käyttäjien yksilöllisten kulutusprofiilien mukaisesti, ja kysyntäjoustotoimenpiteisiin ryhdyttiin, kun koko järjestelmä sitä vaati.

Simulointimalli osoitti, että ennustava kysyntäjousto voi alentaa rakennuksen lämmityskustannuksia 4% lämmityskauden aikana. Suurimmat kustannussäästöt koituvat energiantuottajille, sillä muuttuvat tuotantokustannukset laskivat simulaatiossa 6% käyttäen 15% rakennuskannan pinta-alasta hyödyksi. Huonesimulaatio osoitti, että rakennuksiin voi varastoida dynaamisesti lämpöä läsnäolon, sään ja hintojen älykkäällä ennustamisella. Itsenäisellä huutokauppa-alustalla kysyntäjouston toimintaa voidaan kohdistaa rakennuksiin, joilla on parhaimmat edellytykset siirtää hetkittäin lämmitystehoa. Tämä jako määräytyy kuluttajien mieltymysten ja rakennuksen lämpöhäviöiden mukaan.

Koska ennakoivan kysyntäjouston täyden potentiaalin hyödyntäminen perustuu asiakkaiden sekä tuottajien sitoumukseen, tutkielma ehdottaa konseptia, jossa kaikki osapuolet hyötyvät kysyntäjoustosta. Tutkielmassa käy ilmi, että uusia liiketoimintamalleja voi syntyä varmistamaan kohtuullisen hyödynjaon ja parantamaan lämpökuormien ennustettavuutta. Nämä mallit voivat haastaa osapuolia löytämään uutta arvoa kaukolämmöstä ja -jäähdytyksestä.

Avainsanat kysyntäjousto, kaukolämpö- ja -jäähdytys, dynaaminen hinnoittelu, ennustaminen, optimointi

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I want to thank my intimate friends and relatives who have been beside me during my study path. It has been a great pleasure to meet such an amount of intelligent and ambitious people. With my study colleagues, I have travelled around the world and within Finland to see various technologies in energy business. Every journey has been a great learning experience.

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Helsinki, 5th September 2016

Sonja Salo

Table of content

Units of Measure

A	Heated floor area	[m^2]
A_e	Heated area of the element	[m^2]
a	Thermal conductivity	[m^2/s]
C	Heat capacity	[J/K]
C_e	Heat capacity of the element	[J/K]
H	Thermal conductivity	[W/mK]
h_c	Heat transfer coefficient by convection	[W/m^{2}K]
h_r	Heat transfer coefficient by radiation	[W/m^{2}K]
J	Cost function	[-]
P	DH price	[€/MWh]
Q	Quantity	[Wh]
T_{in}	Inside temperature	[˚C]
T_{out}	Outside temperature	[˚C]
T_r	Temperature of the room	[˚C]
T_{ref}	Reference temperature	[˚C]
t	Time length	[s] or [h]
t_r	Mean radiant temperature	[˚C]
t_0	Operative temperature	[˚C]
T_I	Temperature of the knot	[°C]
U	Thermal transmittance	[W/mK]
V	Variable production cost	[€/MWh]
δ	Active thickness	[m]
ε	Elasticity	[-]
ρ	Density	[kg/m^3]
τ	Time constant	[h]
Φ	Power	[W]

List of Abbreviations

ANN	Artificial Neural Network
AMR	Automatic Meter Reading
CHP	Combined Heat and Power
COP	Coefficient of performance
CO_2	Carbon dioxide
CO_2e	Carbon dioxide equivalent
DH	District Heating
DC	District Cooling
DHC	District Heating and Cooling
DHW	Domestic Hot Water
DSM	Demand-side management
DR	Demand response
EUA	European Union Emission Allowance
ESCO	Energy Service Company
HOB	Heat Only Boiler
ICT	Information and Communication Technology
IEA	International Energy Agency
IoT	Internet of Things
LP	Linear programming
MILP	Mixed integer linear programming
MPC	Model Predictive Control
O&M	Operation and Maintenance
PMV	Predictive Mean Vote
RE	Renewable Energy
TES	Thermal Energy Storage
ToU	Time of Use
VAT	Value-added tax

1 Introduction

The energy business is on the threshold of a new era, as a large number of technologies have recently emerged to mitigate climate change. In this context, smart cities, which retain intelligent building technologies, are evolving. The building sector has been identified by the International Energy Agency (IEA) as one of the most cost-effective sectors for reducing energy consumption, as 35% of total energy savings in buildings can be achieved in space heating (IEA 2011). Energy reductions in buildings would have major effects in Finland, since the building stock consumes 25% of Finland's primary energy, accounting for as much as 64 TWh in 2014 (Statistics Finland 2015). Moreover, as the energy for this building stock is produced either in District Heating and Cooling (DHC) plants, or with other technologies, buildings are seen as major emitters of CO_2e[1]. In order to reduce these emissions, novel building technologies can be utilized to optimize energy consumption. New technologies, such as attic insulation, electricity savings, and heat load control, should enable us to not only increase heating quality but also to simultaneously optimize energy consumption. However, wide daily variation in outside temperature, in combination with time-based load control systems and typical daily consumption patterns may inevitably lead to peak loads during morning hours, as demonstrated in Figure 1 from the artificial DH system simulated in this thesis.

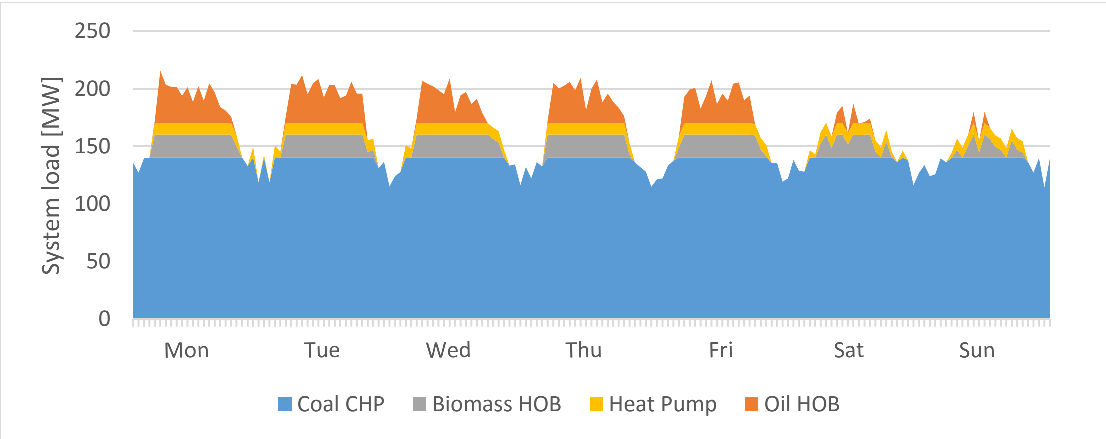

Figure 1: Typical example of daily heat load variation and fuel consumption simulated in this thesis. See Section 5.3.

Figure 1 presents an example of the heat load variation during one week in spring. As seen in the figure, peak heat loads are typically compensated for by fast ramp-up heating plants. Unfortunately, these plants mainly rely on fossil fuels and are therefore expensive to operate. Moreover, they discharge polluting effluents into the atmosphere. One approach for decreasing the demand for ramp-up heating plants is to balance load profiles by exploiting intelligent demand managing programmes. Demand-side management

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[1] The term CO_2e expresses greenhouse gas emissions in terms of CO_2 based on their relative global warming potential.

(DSM) aims to provide economic and environmental benefits by balancing load profiles in an effort to obtain the lowest hourly rate for DHC.

Similar to electricity and water, DHC is seen by the consumer as an unlimited, endless commodity, which can be consumed whenever wanted. This mind-set leads to inefficiency in the market. Nevertheless, DSM enables the consumer to readily participate in efficiency measures. DSM can also give production companies the possibility to operate plants in an economical and environmental manner (Wernstedt, Davidsson et al. 2007). Although DSM has previously been applied to control electrical grids, it has yet to be developed for use in DHC grids.

1.1 Research Objective

This thesis aims to develop an algorithm for controlling heating and cooling loads in various building types. In order to identify the most cost-efficient approach for both the DHC producer and consumer, the model evaluates and integrates various data from DHC systems. Consequently, the research question can be formulated as follows:

"How can high resolution data sets be utilized for Demand-side Management prediction in buildings connected to district heating and cooling systems?"

The data used in this study consists of hourly measured indoor and outdoor temperatures, hourly posted heating consumption, accurate weather forecasts, and social behaviour of the occupants. As DSM does not necessary strive for energy reduction but for a timely shift in heat loads, it can provide an overall cost reduction in the thermal power produced. As a result, another objective is to identify incentives for sharing the value of DSM between the energy company and the customer. As use of the same algorithm for all buildings can lead to a shift in peak loads within the system, and additional algorithm was developed for allocating the short-term DSM targets between the building stock. Therefore, the research question is endorsed by following sub-questions:

"How and why should be predictive DSM applied in DHC systems?"

and

"Where is actual cost saving potential found?"

The thesis is conducted for Fourdeg Oy. Fourdeg is a start-up company which provides smart heating services to increase consumer comfort and decrease energy consumption. With an online learning algorithm, buildings are heated on demand which decreases total energy consumption. Furthermore, with independently acting intelligent radiator controllers, individual rooms can be managed and consumers are able to adjust inside temperature to personal preferences. The algorithm combines historic data, weather forecasts, and consumer occupancy for heating separate rooms in buildings. The target is to provide constant inside temperatures at a minimal cost. With the contribution of this thesis, the algorithm will further optimize consumption depending on a dynamic heating price. By this, cost reduction is not only found via energy reduction but by optimal timing.

1.2 Research Scope

As the framework of predictive DSM, smart DHC grids, and data utilization is extensive, the thesis focuses on the technical constraints and issues on how DSM could be put into practice by the utilization of buildings as short-term energy storage. DSM is applied on the thermal inertia of the building in order to utilize its short-term energy storage potential. Still, approaches on metering the value of DSM business models are provided.

This gives also the stakeholders an opportunity to adjust DSM based on local requirements. However, the need for comprehensive pricing strategies will be accurate in the near future and the implementation of DSM is questionable if customers do not get sufficient economic benefits from demand shifting.

Although alternative technologies for DSM are presented, the thesis focuses in DSM in typical buildings with water radiators. These buildings are seen as short-term energy buffers which can be charged and discharged. DSM can be implemented in smart buildings as part of their information and communication technologies (ICT). These technologies collect, analyse, and exploit detailed data. In a DHC system, such data arise from the consumer side, the producer side, and the environment, such as from the grid, weather conditions and electricity prices. This data can be exploited to develop programs which optimize not only a subset but the whole system. The goal of DSM is to decreases climate impact and raise economic value without causing consumer discomfort.

Figure 2 presents the operation field within a DHC network. The thesis focuses on the actions between DHC producer and end users. These actions are typically paid by the customer, i.e. the legal person which buys the energy from the producer. The producer is seen as the energy company or other producers which provide energy, and the end user refers to the inhabitant in the building unit. By this settlement of the research objective, the thesis neglects further energy efficiency actions and production optimization strategies.

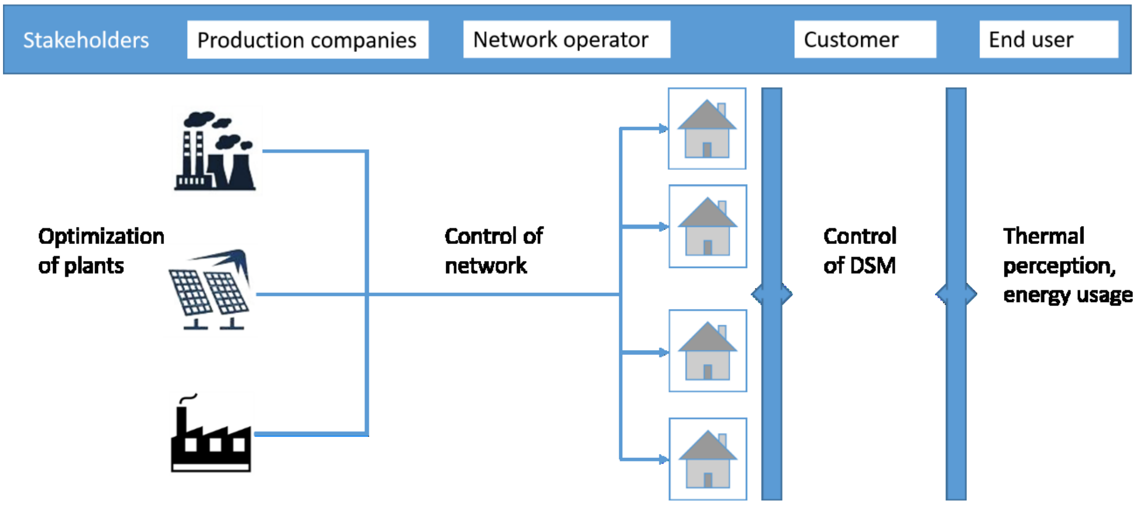

Figure 2: DSM operation field in DHC systems as an illustration of the research scope.

The goal of the thesis is to describe the holistic perspective of DSM in DHC systems. Explicit methods are described and validated but detailed analysis of the differences between methods are not given. Since district heating (DH) has a larger market share than district cooling (DC), the simulations are fulfilled for heating needs. DC is still taken into account as the concept can be equally adapted in DC systems. Furthermore, as the principle of DSM has its roots in electrical ventilation control, i.e. controlling cooling energy, the strategies may not differ in DC.

1.3 Structure of the Thesis

The thesis is structured as follows: Chapter 2 reviews the state of the art of the possibilities to improve DHC systems by smart metering and DSM. In Chapter 3, a description of the mathematical strategies available to determine the thermal energy storage capacity is given. In Chapter 4, this information is used to develop a predictive algorithm which balances the marginal cost of the producer against the marginal cost for the consumer. The marginal costs for the producer are created through a simulated DHC system and the marginal cost for the consumer through the thermal dissipation of the building and a penalty function on inside temperature change.

After describing the methods used in this thesis, the provided dataset was aggregated to the level which enables the simulation and optimization calculations. In Chapter 5, the findings of two simulations are presented. The first simulation optimized whole building units and incorporated these outcomes to the artificial system, and estimations for production cost reductions are given. In the second simulation, each room in a building is optimized based on individual thermal comfort and marginal DH production costs. As DSM has several obligations on a regulated market, suggestions for valuing DSM and a discussion of the business environment are given in Chapter 6. In Chapter 7, conclusions were drawn, research limitations are discussed, and directions for future study are suggested.

2 DSM – High Hopes or Wasted Effort?

The framework of DSM in DHC systems is presented through state of the art literature in this chapter. In the first section, an overview of DHC systems is given, including a description on energy losses within the system and within the buildings. In Section 2.2, upcoming trends in smart grids are discussed and an establishment on linking these trends in a chain for DSM is included. To establish the importance of DSM, the issue of load variation is described in the sequential section. After this, DSM is defined and common analogies between DHC load control and electrical load control are identified and justified for latter applications on DSM thermal systems. The interests of different stakeholders, as well as positive and negative effects of DSM are also presented.

2.1 DHC System Overview

District heating and cooling (DHC) systems include matured technologies which aim to deliver heating or cooling energy to buildings. In a traditional definition, hot water or chilled water is produced at a central plant, which is then distributed via a two-sided pipe system underground to buildings. However, DHC can be also delivered from decentralized plants. In one way or another, buildings served by a DHC system do not require individual boilers or air conditioners but receive energy either totally or partly external[2].

A DHC system consists of production facilities, a grid network and the end consumers. In 2014, DH was produced 34.7 TWh. CHP plants produced 25.2 TWh heat and 12.3 TWh electricity (Finnish Energy 2016a). In Finland, DH is exploited extensively and approximately half of the total heat demand is produced with DH (Statistics Finland 2014). Almost every city and population centre has a DH grid. Therefore, there are more than 150 independent, mostly municipal owned DH companies which differ in strategy, tariffs, contracts, prices, and customers (Finnish Energy 2016b).

DC is defined as providing cooling energy for buildings by a grid system. Cooling energy can be produced, for example, with absorption technique, heat pumps, or a direct heat transfer from deep water sources. DC is one option among other cooling methods and it suits well for dense building areas (Airaksinen, Vainio et al. 2015). In fact, DC in Finland is extended mostly to city centres in large cities, counting 182 GWh in 2015, and further extensions are planned (Finnish Energy 2016b).

Buildings can be connected to DHC either by the regulation of authorities or by a market-based approach (Hellmer 2013). If the decision is made on market-base, DHC is competing against other heating or cooling technologies, such as boilers and heat pumps. If the building possessor has made the investment decision to connect to DHC, he has little possibilities to negotiate prices and delivery conditions, since DHC is seen as a natural monopoly supervised by the Energy Authority (Finnish Energy 2016b). The maximum allowed profit for DHC companies is specified based on invested capital and alternative risk-free investment returns (Syri, Mäkelä et al. 2015).

The main advantages of DHC are high efficiency in heat production, and low level of emissions in centralized plants. DHC has led in general to better air quality in cities and comfortable, continuous energy delivery to its customers. Compared to individual heating

[2] Partly external refers to buildings which possess a hybrid heating or cooling system.

or cooling systems, DHC requires less floor space and less capital investment than other systems (Kontu 2014). Additionally, the possibility of utilizing a wide range of fuels, technology, and storage systems enabled the market leading role of DH. In general, DH consumption interruptions are 1-2 hours in a year which occur mainly because of grid damages and overhaul in grids (Finnish Energy 2016b). To understand the background and targets of DSM, the role of the three participants in a DHC system and their interest in the product, the pricing, and in DSM are described in the next sections.

2.1.1 Production

Finland, as a country with a cold climate and a limited amount of natural resources, has developed a system with high amount of centralized generation power plants. The heat demand in a DHC system is satisfied in the merit order sequence in which the facility with the lowest variable costs is ramped up first followed by the next cheapest plant. DHC systems with a Combined Heat and Power (CHP) plant cover half of the maximum heating power, but provide 90% of the energy demand in a year (Koskelainen, Saarela et al. 2006). The remaining heat demand can be covered by various technologies, such as heat only boilers (HOB), industrial waste heat, heat pumps, and solar heating systems. However, most of the current systems consist of CHP plants and HOBs where the latter are fired during peak demand hours or as back-up boilers (Finnish Energy 2016b).

The main environmental impact of DHC originates from the fuel mix. Finland has a versatile combination of different production facilities. Figure 3 cascades the Finnish fuel mix for DH production. The mix is allocated with a thermodynamic allocation method called energy method (Statistics Finland 2014). This method is one of many distribution methods and are of interest when allocating costs in CHP plants. These are further discussed in Section 4.7.1. The Finnish DHC fuel mix is dominated by fossil fuels. While other high heat demand countries, such as Sweden, started already in the 1980's to renovate its fuel mix from fossil fuels to RE and waste fuels (Kensby, Trüschel et al. 2015), the Finnish renovation is still in its infancy. However, in the recent years DH has become more carbon neutral (Finnish Energy 2016a).

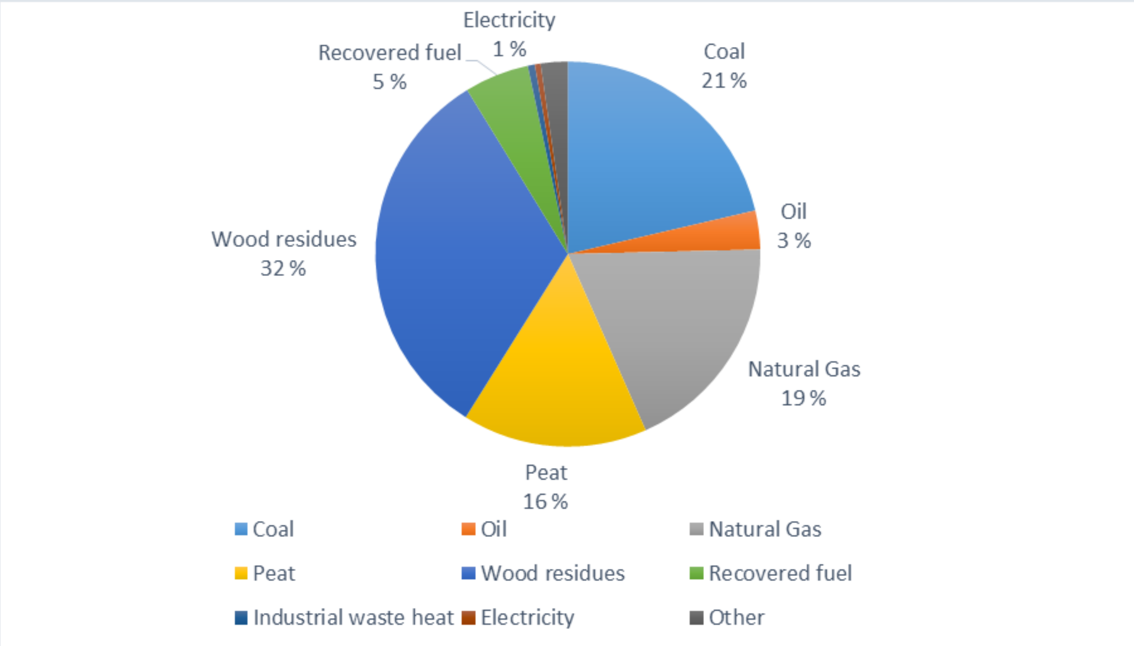

Figure 3: Finnish DH production mix. (Statistics Finland 2014)

When examining studies from different countries it needs to be taken into account that regional differences may cause errors in the importance of the input factors. For instance, differences in income and general energy prices affect the impact of demand elasticity (Grohnheit, Klavs 2000). Climatic resemblances and the relative high share of DHC make the Nordics beneficial for further examination. However, the production structure causes still differences in efficiency approaches. For example, Finland and Denmark produce the majority of DH with cogeneration power plants while in Sweden it is produced with waste-to-energy power plants and heat pumps (Euroheat & Power 2015). Different production structures suggestively affect the marginal costs in different seasons (Sarvaranta, Jääskeläinen et al. 2012). Since Finland uses CHP plants rather than heat boilers for heating demand, the main perspective of energy optimization is based on the optimal production of electricity. Electricity prices are determined at the Nordic electricity market, Nord Pool (Nord Pool Spot 2016a).

The following graphic illustrates a Sankey[3] diagram of the potential energy flows in a DHC system. The width of the lines represents the amount of energy. Excess products, such as unused heating energy, can be recycled in the system with DSM. Realized losses, which cannot be sold to the customer, are directed downwards from the process. The diagram emphasizes that the total efficiency, and thereby total profit, of the system is maximized by minimizing losses.

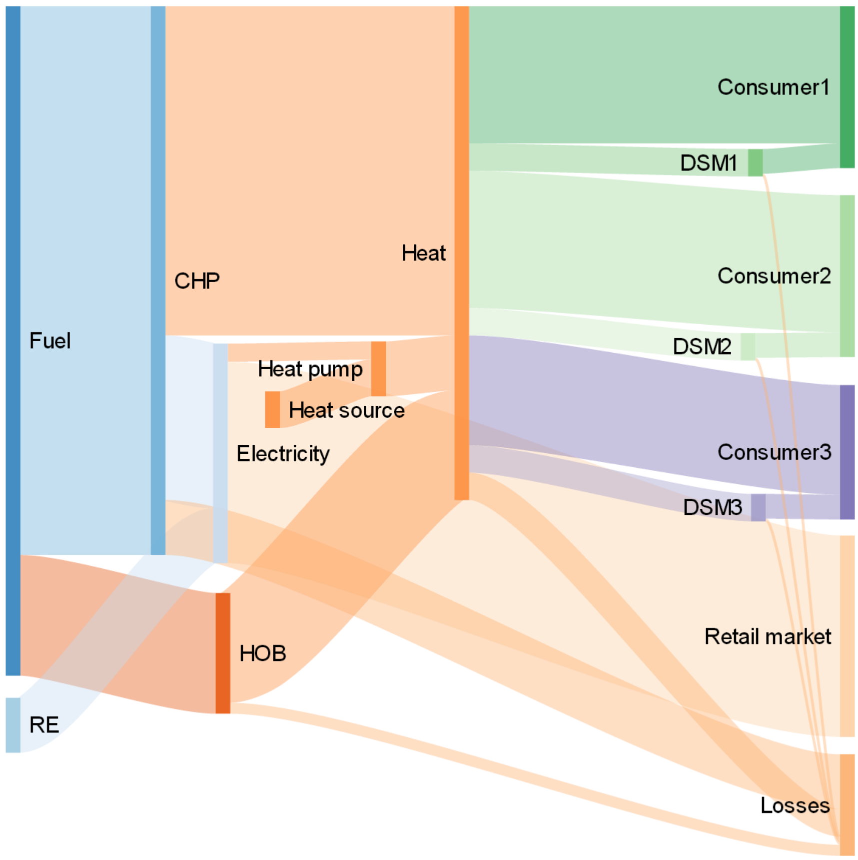

Figure 4: Sankey diagram of DH system with embedded DSM.

[3] A Sankey diagram depicts flow of energy where the width of each flow pictured is based on its quantity.

The Sankey diagram shows that producers receive the best revenue by mitigating losses at every production stage. This mind-set can be extended to DSM by transferring heat streams to customers at every production hour.

2.1.2 Network

A DHC network supplies heating energy from centralized production facilities to buildings via a two side pipe system. DC can be provided by a separate pipeline. The total efficiency of the DHC network depends on the housing density because losses in the distribution grid low the efficiency. The aim of the network is to deliver heating or cooling energy from production companies to the end users with minimal heat loss. Simultaneously, the network aims to minimize disorders and bottlenecks. (Koskelainen, Saarela, & Sipilä, 2006).

Even though DHC is often referred to as a one producer market, external heating or cooling energy providers have the possibility to participate on the market with a separate contract (Sarvaranta, Jääskeläinen et al. 2012). By this, DHC providers are able to utilize also waste heat or excess heat from industrial facilities. Utilizing heat from the industry has shown to decrease DH production prices (Syri, Mäkelä et al. 2015). This leads to an extending demand on pricing heat. Separating DHC producers and the grid into two companies has been studied in the recent years with the conclusion that this kind of solution does not serve the society, the DHC producer, nor the customer (Söderholm, Wårell 2011). This topic s further discussed in section 2.2.2 and 2.2.1.

2.1.3 Consumption

The demand for DHC depends on three components: losses in space heating, losses in domestic hot water heating, and losses in indoor ventilation heating (Koskelainen, Saarela et al. 2006). As energy demand can be investigated in different stages, an overview of heat flow from sources to sinks is given in Figure 5.

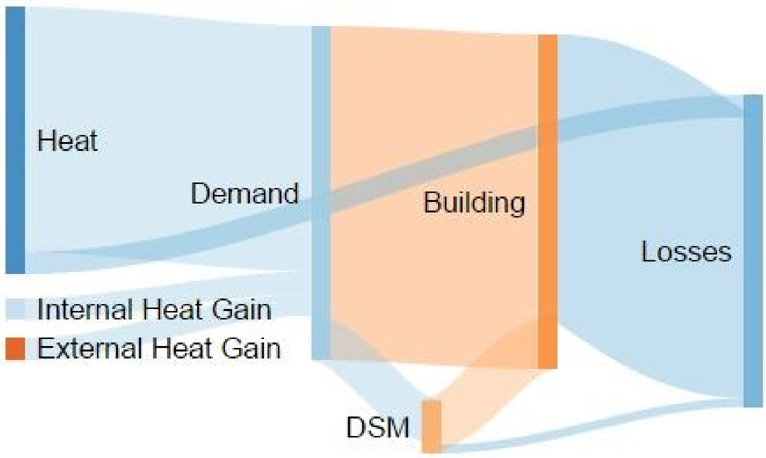

Figure 5: Heat flow in buildings. Adapted from (Seppänen 2001) and further extended for DSM.

DSM represents the flexibility to store heat for a later use. In the figure, heat flows from sources, such as the heat exchanger, and internal and external heat sources to the actual demand of the building. As described in Seppänen et al. (2001) internal heat sources include human occupancy, metabolic rate, and electrical devices which affect load variations during the day. External heat sources in turn are caused by direct and diffuse solar radiation and alternative heat sources.

The amount of energy a DHC system is supplying to buildings composes of three components: radiator heating, domestic water heating, and ventilation heating. DH consumption can be monitored with the specific heat consumption of the building. The specific heat consumption discloses the annual amount of energy used per cubic meter [Wh/m^{3}a] or square meter [Wh/m^{2}a]. By comparing this number to buildings with a similar usage profile, the energy economic efficiency can be estimated (Koskelainen, Saarela et al. 2006).

The DHC network is connected to the substation of the building indirectly with a hydraulic separation, as reported by Wiltshire (2006). The primary side is operated by the DHC company while the secondary side is controlled by the central heating system of the building. The indirect connection allows the DH operator freedom to manage the DH system conditions without unduly disturbing the connected customers. The indirect method employs usually two heat exchangers: one is designed for heating DHW and the other for heating the radiator network. The basic adjustment for the load is executed in the heat distribution centre of the building and the fine tuning is completed through the radiator valves in each room (Ahlstedt, Koskelainen 1995). While former studies have found it difficult to adjust DSM on the whole building, individual control devices are able to execute DSM contingent to the variable heat demand of each room for example via the water radiator valve.

The indoor and outdoor temperature difference affects linearly the amount of heat that is lost by convection and conduction through the building components, including walls, floors, windows and ceilings (D5 Suomen rakentamismääräyskokoelma 2012). This dependency applies only during the heating period. The heat balance of buildings is further discussed in Section 3.1.

The total heat loss due to conduction can be calculated in the following way (Koskelainen, Saarela et al. 2006):

$$\Phi_{conduction} = \sum U \times A \times (T_{in} - T_{out}), \tag{1}$$

where

U is the value of thermal transmittance of each building component [W/mK],

A is the area [m^2],

T_{in} is the inside temperature, and

T_{out} is the outside temperature.

Ventilation losses depend on the ventilation architecture of the building. As reported by Koskelainen et al. (2006, pp. 89-92), losses can be compelling if the buildings are entirely heated up with ventilation, or if heat recovery systems are not installed. Ventilation systems have been implemented in buildings during different time periods. Machine driven ventilation systems without heat recovery systems have been used mostly from 1970 to 2000, and after that ventilation systems with heat recovery are installed. Efficiency actions in ventilation systems have reduced ventilation losses and consequently the specific heat consumption. However, the ventilation heating and cooling possesses still a major share of energy consumption, as seen in Figure 6.

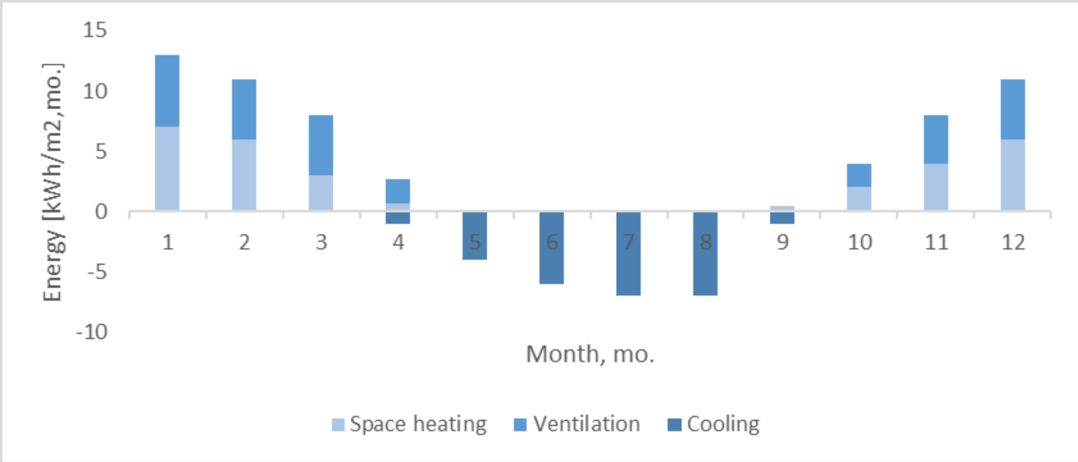

Figure 6: Heating and cooling energy demand in an office building in Vantaa, Southern Finland (Jylhä, Kalamees et al. 2012-05-01).

Operation integers for ventilation are the inside flow temperature, the moisture and the volume flow rate. The flow temperature is adjusted by the radiator fluid temperature and volume flow of air (Koskelainen, Saarela et al. 2006). The loads of ventilation heating are large but the thermal capacity of air is low compared to the capacity of water in the radiator network. However, as temperature change in intake air heating is immediately felt, DSM control shall be done in a moderate manner. DSM studies have reduced intake air temperature by 1-2˚C (Kärkkäinen et al., 2003). As a consequence, for the narrow control window, DSM in ventilation heating is not further investigated.

At last, heating losses through hot tap water usage is investigated. Heating domestic hot water (DHW) does not depend on the outdoor weather conditions but on the social behaviour. This can be monitored especially during summer time when space heating is not required. To secure consumer comfort, DSM activities are not affecting DHW heat load. The required temperature in DHW depends on two factors: comfort demand and Legionella bacteria prevention (Wiltshire 2016). Depending on the space heating demand DHW temperature can set the overall lower boundary for the supply temperature (Hongisto, Seppänen 2005).

2.1.4 Market Development

District heating has a matured market position. Energy efficiency actions have led to a decrease in heating demand per square meter by 30% in the past 40 years (Finnish Energy 2016a). Further decrease in energy consumption has been appraised to decrease by 4-7% until 2030 (Jylhä, Kalamees et al. 2012). However, due to an increase in building stock, DH demand is concluded to slightly increase (Vainio, Lindroos et al. 2015). It is estimated that urbanization causes a growing amount of dense building areas, which are convenient for DH extension. In a scenario analysis by Pesola, Vehviläinen et al. (2011), the price for DH increases depending on the amount of connected buildings to DH systems, investment decisions, and the development of fuel prices. The increasing price can be partly explained by the development of the production stock to contain a high share of renewable energy (RE). The slope flattens out if buildings proceed to be connected to DH networks. As increasing fuel prices are directed to the customer to be paid, energy efficiency conservations attain progressively the customer’s attention. Therefore, the authors estimate that the interest free repayment period will abbreviate.

On the other hand, climate change will milden the Nordic climate so that DC is interesting solution as well. Airaksinen et al. (2015) reports that the cooling demand is growing faster than the building stock in Finland. However, the economic situation is affecting market development more than the actual demand. It has been evaluated that heat pumps will gain more importance due to the ability to convert electricity into heat when electricity price is low (Lund, Werner et al. 2014, Kontu 2014). However, heat pumps are evaluated to subsidise other heating methods than DH (Pesola, Vehviläinen et al. 2011).

The robustness of a DHC grid is challenged with the increasing trend of a decentralized DHC grid network. Energy will not only be produced by traditional energy companies but DH will be as well gathered via excess heat from hospitals, data centres and other facilities which have a cooling need (Vainio, Lindroos et al. 2015). In order to meet these challenges, smart grid systems are developed. These are further discussed in the next section.

2.2 DHC System Prospects

In the past, the energy grid has been functioning like a railway road: Heating and cooling energy was delivered from large CHP and heating plants via many pipe levels to the end user. However, the task of the local grids is changing. The production and consumption of DHC is spreading, as waste heat, thermal solar energy, and other production methods are providing excess energy to the grid. The railway road is changing into a two-way road with oncoming traffic. As a two-way system will be more common, calculation capacity needs to be provided to handle bottlenecks, ensure energy capacity and provide the right refund for the users. DHC systems are facing disruptive technologies which are emerging among following trends: urbanization, customer awareness, climate change and resource efficiency, new comprehensive technologies, and digitization. Especially ICT, big data analytics, and high resolution measurement devices provide novel possibilities to optimize the energy flow and design in a new way. Since these changes can occur, intelligent network systems, or smart grids, as they are often referred to, are evolving.

Smart grids focus traditionally only on electricity. Siano (2014) defined smart grids as *"an electric grid that can deliver electricity in a controlled, smart way from points of generation to active consumers"*. However, Lund et al. (2014) advances that smart grids should be extended to a more extensive complex, smart energy systems, where smart electricity, gas and thermal grids are integrated to achieve system efficiency, identifying suitable energy infrastructure designs and operation strategies. The definition for smart DHC grids can be described as follows: *"a network of pipes connecting the buildings [...]so that they can be served from centralized plants as well as from a number of distributed heating or cooling production units including individual contributions from the connected buildings"* (Lund 2014). This definition sums as well the definition of DHC in general as it takes into account the future decentralized characteristic of DHC grids and the interaction with the consumer.

The characteristic of digitization is an important factor in smart grids. Davido et al. (2009) listed technologies which are marking smart grids systems. These are real time information, two way networks, integration of utility information systems, shifts in customer behaviour, and regulatory changes. Utilities are building new capabilities to capture the potential benefits, which should enhance the daily life of inhabitants.

In smart grids, there are certain constraints which need to be merged and optimized to find value which is satisfactory for all participants. Saringer-Bory et al. (2012) have found economic and technological obstacles which affect the flexibility of smart grids. These contain the liability to meet the demand, legal restrictions on environmental issues, quality parameters, and variable costs for fuels, electricity and emission allowances. Schmidt et al. (2013) has also listed obstacles marked in energy production. These contain minimization of interferences, and fencing of the risk of both internal and external disorders. Disorders, such as material fatigue, can be communicated fast and even prevented with devices with Internet of Things (IoT) features (Mayer-Schönberger, Cukier 2013). The authors expound as well that smart grids enable to operate plants at the maximum capacity and the continual usage of all degrees of freedom for the optimization of energy costs.

DHC consumption is measured through the mass flow of water and the temperatures of supply and return water (Koskelainen et al., 2006). From these measurements it is possible to calculate the energy consumption of the building. As in electricity grids with automatic meter reading (AMR) systems, hourly measured metering systems are increasingly becoming more common. Currently, remote meters automatically send metering data directly to DHC suppliers for pricing and maintenance (Kontu 2014, pp.50). DHC producers can gain from smart meters by having the ability to forecast demand, adjust connection to real load, and distinguish leakages by high return temperatures and peak loads (Schmidt, Basciotti et al. 2013).

Smart metering comprise in addition to the actual energy consumption also measures on indoor temperature, accurate weather data, and behavioural changes from the consumer side. The latter one means that high resolution data is able to notice if a commercial premise extends its opening times, i.e. the demand for energy increases, or if the building has completed a thermal renovation and thus energy or peak power demand decrease. A central question is, who owns the data and who is allowed to take action (SET expert panel 6.6.2016). Further questions regarding smart grids are discussed in the following sections.

2.2.1 Pricing Models

DHC pricing consists generally of three components: a connection fee, a fixed charge, and an energy charge (Finnish Energy 2016b). The connection fee is paid when a building connects to the DH network and is thus a one-time investment. The fixed charge usually depends on the contracted capacity or the contracted water flow and aims to compensate the maximal plant capacity maintenance. The energy charge comprises usually the variable costs of producing DHC which are formed by the fuel mix and variable operation costs. (Koskelainen, Saarela et al. 2006) Some DHC providers have additional cost components, such as a return water temperature fee in order to advice customers to take charge of their DHC devices (Martikainen 2016).

Pesola, Bröckl et al. (2011) report that DHC producers should develop their pricing model in a way which encourages consumers to shift peak loads. This should be performed as easily as possible and transparently in order to meet EU's targets on energy efficiency. However, a progressive model should be introduced only to large consumers because it is difficult to allocate cost savings in building apartments. Real time pricing tariffs reflect the marginal cost of energy production and therefore, these tariffs vary as the expected load varies (Abdulaal, Asfour 2016). This would signal customers to make savings in heat consumption during expensive heat production periods, which would lead to more rational heat consumption reduction and heat saving measures (Henri Mäkelä 2014).

More precise metering systems allow to develop DHC forecasting models and enable in the future real time pricing. Therefore, novel pricing structures for DHC are studied. Difs et al. (2009) presents that dynamic pricing schemes, which are based on marginal heating costs, give better information to customers. This encourages customers to more rational DHC consumption and heat saving measures. However, in large systems with multiple DHC producing plants and a large network structure, dynamic pricing tariffs can be difficult to estimate and the costs can also vary over the season (Difs, Trygg 2009, Korjus 2016). These factors complicate the transparency obligations.

DSM can be considered in various conventions, which raises pressure on flexibility and transparency on DH (Valor Partners 2015). For example, DSM can be embedded in hybrid buildings in which the building automation would automatically shift to the other heating method during high DH prices (Pesola, Bröckl et al. 2011). If DSM is implemented to achieve peak load cutting on a large scale, DHC pricing should be adjusted for attracting buildings to participate in DSM. On the one hand, customers emphasize on the voluntariness of participation and demand for sufficient compensation (Manninen 2014). On the other hand, DHC providers want to pay benefits retrospectively based on actual cost savings (Valor Partners 2015).

2.2.2 Open Heat Market

An open heat market is a concept which provides the possibility to utilize excess energy from industrial processes and buildings connected to a DHC network. It is interesting for DSM because both concepts include aspects of marginal cost pricing and the effective exercise of resources. An open heat market refers to unfasten distribution systems to competition in order to manage increasing price trends and bring about greater variation in properties and agreement structures (Dahlroth 2009). Analogous to the liberalization of the electricity market, a DHC system could also contain several independent producers and one grid operator. This could increase interest in energy optimization. Furthermore, in a two-way DHC system, customers can be encouraged for further heat load optimization, as excess heat can be fed to the grid.

As described in the previous section, the rigid pricing system is not transparent towards the customer: it does not contribute on formation of heat provision costs which cause dissatisfaction among customers and decreases cost efficiency (Pesola, Bröckl et al. 2011, Sarvaranta, Jääskeläinen et al. 2012, Korjus 2016). Nevertheless, Mäkelä (2014) states that a dynamic price for DH and an open district heating system would lead to a more comprehensively efficient heat market by enhancing resource allocation. Therefore, novel methods for opening the heat market are found to be beneficial for all parties. Further research on this topic by Syri et al. (2015) indicates that DSM in DH systems could provide an attractive solution to reduce peak production facilities which are most expensive from the marginal costs. Remarkable cost and fuel savings are possible to achieve with mutually beneficial business models.

The concept of open heat markets is starting to have commercial applications. In Stockholm, Sweden, an open heat market is launched in which recovered heat is recycled to residential buildings (Dahlroth 2009). These markets have an hourly changing price for DH but these prices are only available for the external heat providers. Stockholm's DH is initially provided by five energy companies. These providers are differing in size, plant design, and actual location within Stockholm. By introducing an open DH market, heat providers can feed energy to the network when it is most profitable for them. In the city of Espoo, Finland, a single-buyer concept has been piloted by utilizing excess heat from hospitals (Fortum 2013). At present, Fortum has extended the share of renewable and external heat sources from less than 1% in 2014 to a predicted 30% in 2016 (Fortum2016a).

2.2.3 Big Data Analytics

Smart grids utilize ICT to gather input from their environment, such as the behaviour of suppliers and consumers, in an automated fashion to improve the efficiency, reliability, economics, and sustainability of the production and distribution of energy (Lund 2014). This technique is broader known as big data. Among many definitions of big data, Mayer-Schönberger and Cukier (2013) offer points on what can be done with the data and why its size matters: "*The ability of society to harness information in novel ways to produce useful insights or goods and services of significant value*" and "*things one can do at a large scale that cannot be done at a smaller one, to extract new insights or create new forms of value*". Although the data volume is a widely used factor for qualification of the big data, when it comes to big data analytics there are a few other important attributes i.e. variety, velocity, valuation and veracity (Laney 2001). Data analytics can be utilized for various consumption pattern and consumer demand identification and analyzation.

Lund (2014) reports that smart grid programmes are able to measure temperature, pressure and flow of the heating fluid. Additionally, they collect outside temperature data, weather forecasts and production conditions from the network. The programs within the smart grid are enabled with the development of big data analytics. Big data analytics is a way to collect, analyse and evaluate large volumes of data. The idea behind it is to deal with different kind of data and connect automatically to a broader system. Big data analytics feature a wide range of data analysis techniques, such as statistical analysis, data mining, machine learning, natural language processing, and data visualisation (Russom 2011). For these growing number of requests for data analyzation the development different measuring techniques, including sensor and model based techniques, have enhanced (Kontu 2014). In addition, a comprehensive platform which deals with optimization requirements needs to be developed. One approach to manage small load amounts is to combine these in a virtual power plant (VPP) platform.

2.2.4 Virtual Power Plant

A VPP consists of an intelligent hardware tool at the power plant, a data transmission route and a user interface which can configure, direct and manage several remote and decentralized energy resources. These devices collect data throughout about the disposable power output, quality of the power, steering parameters and the state of the plants (Zurborg 2010). The goals of the concept are to increase flexibility in the grid, decrease local load fluctuation, and therefore postpone grid investments.

VPPs aim to connect decentralized plants, such as photo voltaic plants, wind energy, and small water plants, through ICT to a coordinated system in order to optimize the energy mix in an economical and environmental way. However, the concept of VPP can be utilized also in large centralized plants, such as in France's nuclear power plant network (Ausubel 2010). In electrical grids, this coordination is utilized for retaining the frequency of the grid. These are also commercially launched (Lichtblick 2016, Fortum 2016b). In the latter example, hot water tanks in buildings are utilized as thermal buffers which match heating requirements with high spot prices.

The same concept could be implemented into DHC systems when taking into consideration that DHC systems are local and the network is illustrative. DHC systems are already centralized managed but ICT and data utilization increase load and demand prediction. VPPs are especially of interest because of the actors involved in a VPP system independently and simultaneous make decisions on the market. In smart grids, utilizing VPPs can modify the entire business model for producers and network operators (Zurborg 2010). In this model, generation companies are not owning plants but retailers, i.e. third party actors, can own entire sets of VPPs that they can leverage against the retail market. These can also facilitate a two-way energy flow as customers can bid energy into the market through the illustrative network.

2.2.5 Load Variation

Demand and load are utilized in this thesis as two concepts that are to a great degree similar but not equal. “Demand” means the amount of energy or power required to fulfil the consumer’s needs, whereas “load” means the amount of energy or power delivered to the customer (Kensby, Trüschel et al. 2015). In most cases, fulfilled demand is equal to the load in an energy system. However, unfulfilled demand can occur unintentionally due to failures or limitations in the energy system or due to an intended active strategy. In other words, a consumer can have a high power demand but not necessarily a high power load if the outtake from the grid is limited. In addition to the advantages of utilizing the technologies in smart grids which were discussed in the previous section, smart grids enable the prediction and prevention of load variation (Gadd, Werner 2013b). At present, heat accumulators are rare in households so that consumption is reflected directly to the heating network (Koskelainen, Saarela et al. 2006).

As stated in the previous section, load variations have an influence on the economic and ecological operation to DHC production companies. Gadd and Werner (2013a) distinguished several backgrounds for load variation in DH networks. First, outside temperature incorporates a steady temperature-dependent load. Seasonal changes lead to different consumption annual patterns. In addition, short-term fluctuation in outside weather, such as transient heat transmission, wind, clouds, and solar radiation, affect the demand for DHC. Temperature can change rapidly which influences daily load variations. These relations are assessed by Gadd and Werner (2013a) where 20 Swedish district heating networks were evaluated as shown in Figure 7. The study presents that heat loads vary hourly between 3-6% of the annual volume and daily heat load variation are of the magnitude of 17-28% in a DHC network occurred on a daily level.

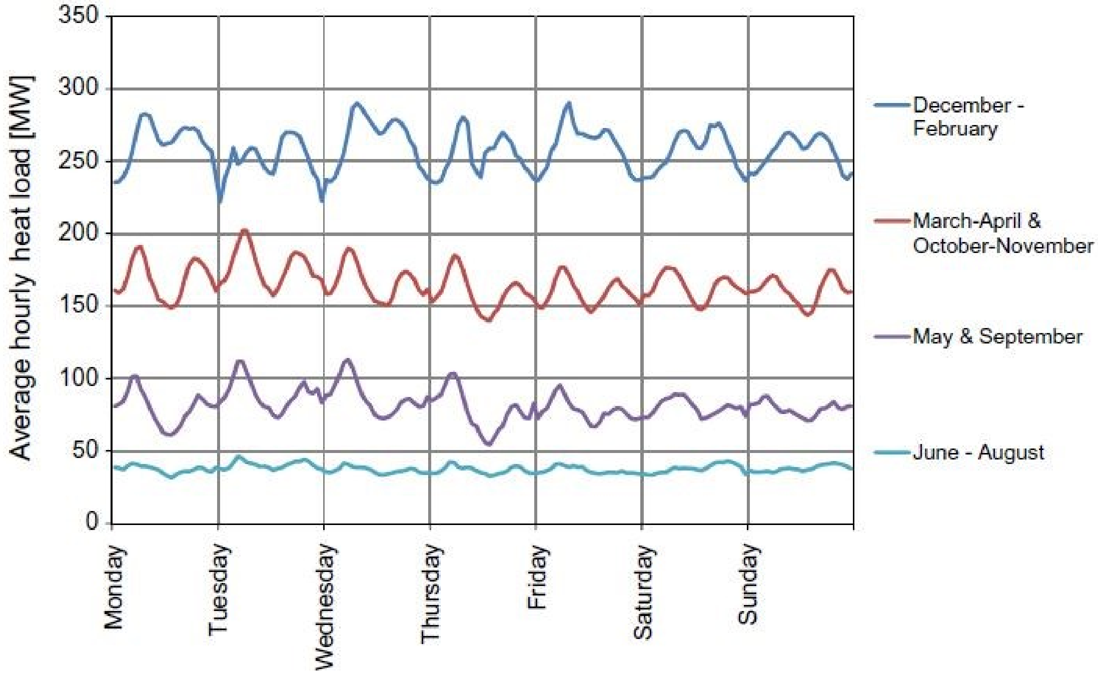

Figure 7: Daily heat load variation for four different seasons (Gadd, Werner 2013a).

Gadd and Werner (2013b) analysed in an additional study the daily and annual heat load patterns in different buildings. Inside-outside temperature differences in winter led to larger heat loads. During the spring and autumn period, the heat load peaks during daytime are less, but they have a sharper spike due to the solar incident radiation. As for the summer period, DHW consumption dominates the heat demand, and hence very small difference in heat load pattern are observed. Even though the outside temperature is changing on occasion, it is possible to predict it via average temperature models (Dotzauer 2002). Furthermore, by use of more accurate weather forecasting models, the daily, weekly and monthly changes in temperature, humidity, radiation and wind are estimated.

Finally, energy saving strategies, such as indoor temperature decrease during night time and weekends, lead to demand variations. These actions can be also predicted. The initial thought behind night setbacks is to lower indoor temperature during nights when the outdoor temperature is also lower and thus decrease the inside-outside temperature difference (Kensby, Trüschel et al. 2015). Consequently, energy consumption is decreased. These have been found beneficial in buildings with individual boilers, but the total benefit cannot be drawn in complex DH networks with cogeneration plants (Airaksinen 2016). However, Gadd and Werner (2013b) state that the amount of heat load reductions due to night time setbacks correlate strongly with the time constant of buildings. The time constant refers to the time in which indoor temperature reduces until 63% of the initial temperature is left (Seppänen 2001). It is a measure of how rapidly a temperature change occurs with exponential decay function. A larger time constant results from increasing insulation and airtight building envelopes (Seppänen 2001). These are further discussed in Chapter 3.

DH systems which contain a considerable number of buildings with night time setback settings can result in large peaks in heat demand in the morning hours (Gadd, Werner 2013b, Kensby, Trüschel et al. 2015). A simulation study by Schmidt et al. (2013) regarding a DH network in Austria investigated the effects of applying DSM strategies to buildings utilizing night setbacks. The buildings were controlled so that they recovered from their setback at different hours. The researchers evaluated that as much as 35% peak reduction could be achieved if applied to the overall DH network. Further assessments on load control are discussed in the following section.

2.3 Demand-side Management Concept

Balancing load profiles means to shift loads in time to decrease peak loads and create an even load profile. Demand-side Management (DSM) refers to the objective to influence the consumption behaviour of the consumer so that the total system usage is optimized. In other words, DSM provides the dynamic ability to par demand to supply. DSM can be seen as the overall notion for energy efficiency in this sense. DSM incorporates energy reduction, peak load shifting and curtailment, and thereby reduce long-term capacity needs (Johansson 2014, Gadd, Werner 2013a, Kärkkäinen, Sipilä et al. 2003). In electrical systems, one subcategory of DSM is demand response (DR) where the target is to manage the heat load [W] rather than the energy consumption [Wh]. This is achieved by short-term reductions in peak demand. Short-term in this sense is limited to a time frame ranging from one hour to a few days.

The main objective in this thesis is to examine DSM actions in DHC grids by shifting peak loads in time. Time shifting can be fulfilled by heating up a heat storage within the grid and in the buildings before the peak load or by delaying DHC provision. Other methods are energy conservation, strategic consumption increase, and changing the end usage of energy in certain times (Koskelainen, Saarela et al. 2006). Since thermal and electrical energy usage vary timely, the dependency of electrical energy in CHP plants is mitigated by storing additional heat for later usage. With these thermal energy storage (TES), electricity can be generated in CHP plants also in times with less heating need. Koskelainen et al. (2006) expose that energy costs of DH are decreased by loading storage units when the marginal cost of production is low and discharging at high marginal costs. Furthermore, peak load boiler usage is decreased in short-term peak hours. However, of the studies are produced for unique DHC systems which cannot be directly proposed to be universal.

Load balancing has been studied for over 30 years. The building capacity which could be controlled has been estimated to be 30-40% from the connection capacity by including only 10% of the consumers to the control system (Ahlstedt, Koskelainen 1995). One of the first studies which developed load balancing to DSM resulted in 20-25% of maximum heat load reduction (Kärkkäinen et al., 2003). In this study, the thermal capacity of the radiator network and the massive building structure enabled reduction times of 2-3 hours at a clip with reasonable indoor temperature changes. Both in Ahlstedt's and Kärkkäinen's explorations, load shedding, i.e. deliberate control of consumption, was fulfilled with time based control devices which are restricted in flexibility. These control devices cannot take the influence of internal and external heat sources or sinks into the DSM programme. In the first wave of DSM programmes, immature measurement and verification devices limited the large scale implementation, causing programs to be exclusive for the largest customers. However, the next wave of DSM is more promising with the increasing penetration of smart meters and ICT (Davido, Tai et al. 2009).

Johansson and Wernstedt (2007) have studied real-time implementation of load control. A residential area in Karlshamn, Sweden, was the subject of a pilot test where DSM was implemented in the form of agent-based load control (Wernstedt et al., 2007). It is concluded that direct load control is imperative in order to attain desirable levels of response. In further studies by Johansson and Wernstedt (2010), control was distributed among agents on three levels: the production level, the cluster level, and on the individual consumer level (Johansson 2014). These agents monitored and controlled first the local systems and then communicated with each other to achieve system-wide peak reduction and optimization. The system displayed the potential for reducing peaks as well as reducing the energy consumption by 4%, even though the thermal storage capacity was only partly exploited (Johansson, Wernstedt et al. 2010). Peak load reductions of approximately 15-20% and energy savings of 8% were achieved. A subsequent larger test of this technology was performed in three major Swedish district heating systems in which substations serving one to several buildings each were included in this test (Johansson, Wernstedt 2010). Intelligent control devices can predict the effect of other heat sources on the indoor temperature and thereby avoid futile caution.

Based on former assessments on DHC systems and DSM, four key stakeholders can be distinguished. As shown in Table 1, the major players in DSM are end users, i.e. consumers, real estate possessors, i.e. customers, and DHC producers. Producers can be energy companies, but in an open heat market also customers can be producers and therefore they are not further separated.

Table 1: An illustration of stakeholders within a DHC system, their main interest and how it may be achieved.

	Interest	**Practice**
Society	Emission reduction	Regulation and education
	Tax income	
	Energy poverty mitigation	
DHC producer	Cost minimization	Operation optimization
Customer/real estate possessor	Cost minimization	DSM
End user/consumer	Cost minimization	DSM
	Comfort maximization	Prediction and individualization

Even though the ambitions of the stakeholders in DSM are different, one factor can be pointed out: cost reduction. However, the multi-objective preference of the end user is affecting the realization of DSM. These stakeholders as presented in the table are further analyzed in the thesis. Especially the difference between customer and consumer should be emphasized. Contemplating Table 1, the next sections discuss DSM with the target to meet the interest of stakeholders.

2.3.1 Potential of DSM

Valor Partners (2015) investigated the current status of DSM in DH systems for the Finnish Energy Authority. The report has summarized several positive effects of DSM, such as:

- Reducing the generation margin, i.e. the mismatch between production and demand
- Reduced load variation
- Better fuel economy
- Decrease of peak load boiler utilization
- Fewer starts and stops in heat generation plants
- Increased security of energy supply
- Reduced temperatures of return water
- Less need to invest in peak load boilers and grid
- Operate combined CHP plants depending on electricity price
- Operate heat pumps and direct electrical heaters in DHC systems based on electricity price
- Decrease in environmental harmful emissions

These aspects can lead to direct economic benefits but do not occur automatically. Many of the above mentioned advantages and their obligations are discussed in the upcoming sections. The aim is to find the balance between the thermal comfort of the consumer and the sufficient load control within DSM has the largest affect the DHC system. Eliminating daily heat load variations can lead to less use of the peak load boilers, less need for electricity for pumping energy, easier optimization of the DHC system operation, and less need for maintenance because of the smoother use of heating plants (Gadd and Werner, 2013a). The more marginal costs of production differ between plants in a DHC system, the higher benefits are achieved from DSM (Valor Partners 2015). The start-up and maintenance costs of the HOBs are also significant additional cost items for DHC companies (Wernstedt, Davidsson et al. 2007).

Furthermore, balancing load profiles refer also to the optimal utilization of heating generation in the system. This means that CHP plants or heat pumps are utilized when the price for electricity is high or low and hence the costs of producing electricity or heat are minimized. Load management can be used in relation to CHP plants in order to synchronize peak demand in electricity and DHC. This technique is profitable for heat suppliers, since they can match their production with high spot prices on the power market (Johansson, Wernstedt et al. 2012).

A further advantage is the possibility to reduce the returning temperature in a DH system. A Swedish pilot test by Wernstedt et al. (2008) indicates that the average return temperatures were reduced by 2 °C while the system was in operation. The study exploited DSM with agent-based optimizing algorithms. The most important factor in reducing returning temperature is that the DH substations are well dimensioned and regulated. Therefore, by reducing peak loads, the system can be better sized and optimized (Wernstedt, Johansson et al. 2008). With the same mass flow, the system can increase its efficiency. Reducing the average return temperature in DH pipes leads to better fuel economy and increases the efficiency of heat plants (Schmidt, Basciotti et al. 2013).

Furthermore, thermal energy storage offers the chance for extended CHP operation based on to the electricity market price without wasting the by-product heat. At times of low heat demand, the thermal energy storage will be charged. The accumulated thermal energy is then exploited to cover the peak load of the heating system in times of higher heat demand or when the CHP unit is not in operation. As an additional benefit, this operation mode of CHP with heat accumulation enables longer annual operation times of the cogeneration unit and reduces the inefficient use of heat-only boilers for peak load coverage (Verda, Colella 2011).

DSM affects primarily the heat load during average heating period (Difs, Bennstam et al. 2010). These times occur during spring and autumn when heat is produced with base load boilers and peak load boilers are started for short-term demand compensation. The reason why low heat loads are not affected is that during the summer months almost no space heating is required, only tap water is utilized. On the other hand, high heat loads are not controlled during winter months because the building needs to be heated continuously.

2.3.2 Elasticity in Economic Sense

In economics, supply and demand of a product or service are determined by the price. If prices change after the market has found an equilibrium between price and quantity, the change in quantity can be represented with price elasticity. Elasticity ε is defined at a market equilibrium point (*Q,P*) as the relative change in quantity is ε times relative change in price (Weitzman 1974):

$$\frac{\Delta Q}{Q} = \varepsilon \frac{\Delta P}{P}, \tag{2}$$

where

Q is the quantity [Wh], and

P is the price [€/MWh].

Elasticities are the most widely used concepts in economic modelling to describe the demand for goods and services as a function of income and prices. Demand elasticity, in economics, refers to how sensitive the demand for a good or service is to changes in other economic variables. Elasticities greater than one are called “elastic”, elasticities less than one are ”inelastic”, and elasticities equal to one are “unit elastic” (Weitzman 1974).

At present, DH demand is in the most countries price inelastic (Hellmer 2013). After selecting DH as the heating medium, the customer cannot influence the pricing scheme. In theory, customers will therefore buy the needed amount for any price. The production company strives towards the minimization of production costs and meeting the energy demand. At present, the customer has marginal opportunities to adjust energy demand, and hence form an individual demand curve, if the price signals do not reach the actual end user of thermal energy.

The following graphics represent the background of DSM in the energy sector. In the graphics, *D* responses for demand [Wh], *Q* for quantity [Wh], *t* for time [h], and *P* for price [€/MWh]. As seen in Figure 8, DHC price is theoretically determined depending on marginal costs which are increasing stepwise depending on the merit order of the power plants.

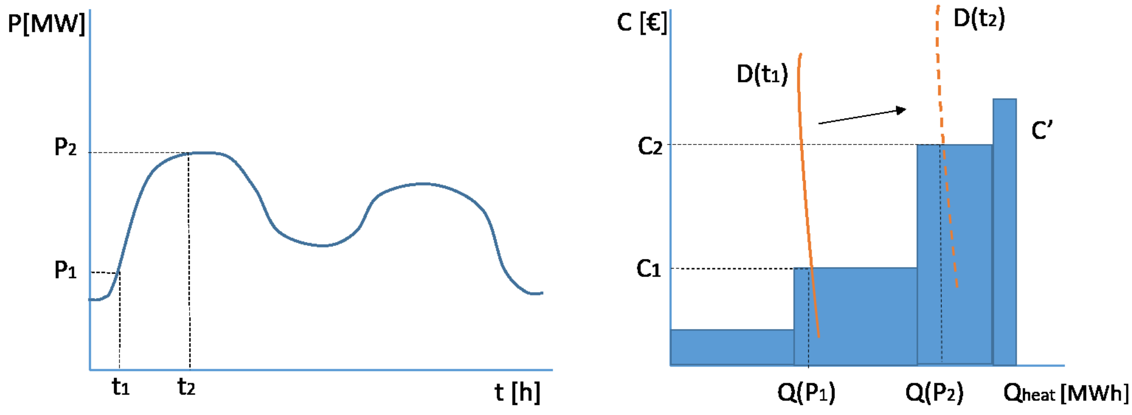

Figure 8: Load variation and cost of energy production.

The effect of DSM can be seen in Figure 9: Even though the amount of load is decreased by a small amount, it can avoid the on-ramping of a HOB and decrease the overall cost of DHC in the system.

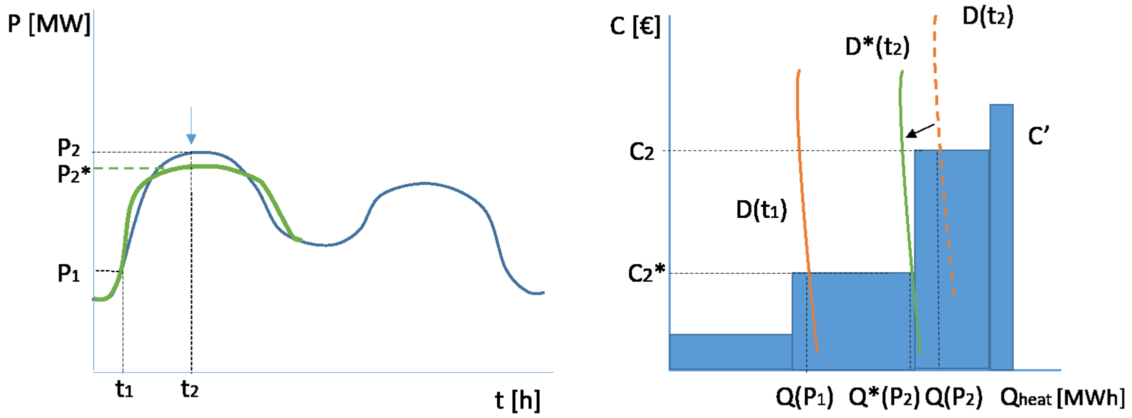

Figure 9: Load variation with DSM impact and cost of energy production.

From the perspective of the DHC producer, heat load should be kept at a steady heat load of $Q^*(P_2)$. By this, the energy company could maximize its profits by minimizing marginal costs. In contrast to an energy reduction concept, the demand shifting approach targets to have minimal impact on preferred comfort conditions by increasing the buildings' thermal inertia prior to the temporary reduction in the radiator loads. As seen in Figure 9, demand was shifted both forward and backward from the peak load hour. The controller algorithm shifts load forwards an upcoming peak price and shifting demand to the future if at a current peak price. In Abudaal (2016) these are called backward demand shifting and forward demand shifting.

This chapter summarized demand elasticity from the producer's perspective. DSM is not only viewed from the producer's point of view, but the total benefit of society should be considered. In order to receive a deeper understanding on DSM from the DHC perspective, the upcoming chapter describes how DSM, or more precisely demand response (DR) is implemented in the electricity sector.

2.3.3 DSM in Electricity

Shifting elasticity liability from producer side to consumer side is an actual topic in electricity systems due to the liberalization of electricity market (Ahonen 2016). This can accelerate the development of DSM in DHC networks. DSM focus on improving the efficiency of the system by shifting or reshaping load, by reducing peak hours, or by contributing to spinning reserves and thus save electricity (Zurborg 2010).In contrary to DSM, the main objective of DR is not to save electricity but to shift peak demand by smoothening the demand curve.

Since electricity as an energy medium is in general more valuable than heat, many energy efficiency studies have focused on electricity. Electricity and heat share many common characteristics and therefore the gained knowledge in electrical demand elasticity can be transferred into DHC systems. However, there are many differences which have an influence on the behaviour of these systems. Therefore, this section introduces first the major similarities and differences between electricity and DHC systems, then it discusses different concepts related to DSM in smart electricity grids, and how these concepts could be implemented into DHC systems.

First, both electrical and DHC grids are demand driven in the developed countries. This means that customers are used to consume electricity and heat at any given time (Kensby et al., 2015). Electricity and DHC systems differ more than initially expected. The DHC producer has the liability to provide heating or cooling energy at any given time and price. While power can be brought from the Nordic electricity market, heat must be always produced locally. On the other hand, this characteristic gives the producer the ability to operate in a natural monopoly.

Next, heating energy is transported via a fluid from the producer to the end users by using mechanical pumps. Hence, it is much slower than how electric energy is transferred through electric fields associated with electrons in the metal wire. It is also more robust as frequency regulation to the grid and fine-tune the balancing between supply and demand in the grid are not required. Electricity grids are spread widely also in rural areas. In addition, decentralized electricity generation, such as wind energy, is produced outside of cities. DHC is on the other hand can be transported only short distances because of its high energy density. This means that DHC is produced and consumed only in local areas and they are separated from each other. Another important factor is that heating energy is not as crucial as electricity: short shortages in the DHC grid are hardly noticed. At last, heating energy is easier to store than electricity and techniques are already settled. Different thermal storage options are further discussed in Section 2.3.6. A more detailed description of the main differences between electric and heating grids is introduced in Table 2.

Table 2: Analogy between electrical and thermal energy in smart grids (Schmidt, Basciotti et al. 2013, Koskelainen, Saarela et al. 2006, Kensby, Trüschel et al. 2015).

Smart electrical grids	**Smart heat grids**
Frequency and voltage conversation Boundary conditions: ± ΔU and ±Δf 50Hz (EN 50160)	Temperature and pressure conversation Boundary conditions depending on contract
Production = Demand + Losses - Demand driven, customers are used to consume energy at any given time	Production = Demand + Losses + Storage - Demand driven, customers are used to consume energy at any given time
Market model - Grid: regulated, natural monopoly - Energy: free market	Market model - Grid: regulated, natural monopoly - Energy: Seldom other feeders
Flexibility - Fast change in demand and supply - Shortages noticed immediately - Capacity market - Electric cars, power to gas etc. - Flexible tariff models	Flexibility - Slow change in demand and supply - Shortages noticed in DHW - Otherwise broader operating environment - Steady energy prices
Smartness - Obligatory AMR meters - Intelligent and optimized electricity system - Usage of flexibilities - Smart buildings	Smartness - Smart metering becomes more frequent - Diverse stage of development in system optimization - Smart buildings

DR denotes to *"changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time"* (DOE 2006). In the short run, DR leads to economic benefits by promoting the interaction and responsiveness of the customers. In the long-term, it lowers peak demand and therefore reduces overall plant and capital cost investments (Siano 2014). Practical examples include the timely shift of loading electric cars, utilization of washing machines, but also thermal demand shifts by controlling direct electrical heaters, heat pumps, and ventilation (Järventausta 2015). These thermal demand shifts can be achieved with predictive control algorithms based on ToU electricity pricing (Gayeski 2010).

Traditionally, balance between supply and demand is achieved by regulating the power output of the generators. However, when RE's share in the electricity system increases, and commercialized electricity storage technologies are still in its infancy, regulating possibilities are limited. Therefore, DR aims to compensate variable load with automated control systems (Järventausta 2015).

To attract a large amount of consumers to a load management event a flexible tariff model needs to be developed. The program Minimal Emission Region (MeRegio) in Germany is testing electrical load profile distribution through price signals with a market-based approach. For this sake a dynamic hourly based tariff system was developed. The target is to develop DR concepts and put them into practice in an inclusive network (MeRegio 2016). The study comprises decentralized producers, consumers and intelligent storage systems with ICT. Thereby, consumers are encouraged to participate actively in peak load reduction, load shifting, and energy conservation. In this concept the consumer decides at which time and how much electricity is taken from the grid or fed into the grid.

Whereas everyday consumer occupancy can be predicted via automated sensors, unique happenings, such as vacation, can be taken into account through an interactive system with the consumer. MeRegio offers a practical example on DR where learned lessons can be avoided in DHC systems. Some parts of the concepts could be implemented in DHC systems if uncontrollable production, such as solar radiation energy and industrial surplus heat will dominate in the heating network. (MeRegio 2016)

Load control can be realized with many technological solutions, such as device-specific IoT solutions, or by utilizing AMR systems (Järventausta 2015). The first is currently a disrupting trend in the smart device industry while the latter allows the transformation of regular invoicing based on the actual consumption instead of regular assessed invoices. AMR enables the shift of constant pricing schemes into hourly varying electricity prices depending on the day-ahead market prices at Nord Pool.

Especially predictive DR in electrical heating systems has been investigated for the similarities in DHC radiator heating. Approaches to avoid electrical heating during expensive electricity price periods have been tested with Internet connection for remote monitoring and control of heating systems (Palola 2016). In an earlier study, Pavlac et. al (2014) introduced controllers and strategies for adjusting air cooling settings in accordance to rises or declines in hourly electricity rates. The authors applied demand shifting for utilizing the buildings' thermal storage while considering the consumer's comfort-tolerance level. They noted that precooling reduces the deviation from thermal comfort levels in DR periods.

Energy companies have started pilots that aim to develop DR services for electricity consumers. Helen Oy has a pilot service which acts as an emergency reserve. This reserve switches automatically electric heaters in households off for maximum 15 minutes (Helen 2014). Fortum Oy launched a similar pilot where 70 electric heated households with thermal water storage units forming a VPP and working as a part of frequency-controlled reserve system. Fortum Oy announced that it has a power reserve potential of 300 MW in heating systems whereas the overall average electricity consumption in Finland is 10000 MW. (Fortum 2016)

Similar to former electricity invoice formation, DH was also estimated with regular invoices and afterwards separately corrected. When investigating various DHC provider's web pages, hourly remote measurement devices become more common also at DHC connected buildings. However, these are offered for the whole building and are not separately offered to each apartment. Therefore, individual customers in residential buildings are not insufficiently included in energy efficiency actions.

2.3.4 Supply Elasticity

In district heating, energy can be stored and controlled either on the producer or on the consumer side. By storing heat, the flexibility of DH increases. Solutions on the producer side are controlling varying loads with the DH grid network or by separate heating tanks. On the consumer side heat can be stored as well in separate water tanks of by utilizing the building's thermal inertia for heat storage purposes. The main purpose is to achieve steady load profiles in the DH grid. (Henze, Krarti 2003) Before understanding the impact and significance of DSM in buildings, also other elasticity actions in the DHC grid should be investigated. DH producers have the possibility to utilize the sensible heat storage potential of DH grids for elasticity purposes. This is done by advanced control techniques which overload the grid when peaks are approaching, and unload the grid during peak consumption. A study in Austria realized a TES capacity of 900 kW in the grid, and by utilizing it during morning peak hours lead to 15% peak load reductions. However, peak load reduction potential is limited by the grid capacity. This limitation leads also to a distribution loss increase of 0.3% without beneficial effects on peak load reduction. (Basciotti 2011) Furthermore, varying the temperature in DH grids have been found to increase stress and earlier fatigue of pipes.

Central water storage tanks are often installed next to the heat production units. Another case study by Verda and Colella (2011) show that the integration of a 3000 m³ central water storage tank is able to reduce the peak load in the morning by 100 MW making it unnecessary to use the back-up boilers. Utilizing storage tanks lead also to primary energy savings, but the investment cost of these TES is appraised to be 2400 €/m³ (Verda, Colella 2011). It should be also noted, that large storage tanks are built due to pressure differences next to the heat plant and thus grid risks and bottlenecks are not decreased (Kensby, Trüschel et al. 2015).

Johansson et al. (2012) equated thermal storage potential of buildings to hot water heat tanks. They report that a sufficiently large group of buildings controlled by a DSM operator is comparable to any storage tank without costs on installation and maintenance. The researchers have also found benefit in the flexibility of TES in buildings, since heat load changes are only limited in time by the speed of the connecting valve. Kensby (2015) presents similar economic results and points out that storage tanks are located usually besides CHP plants which consequences that these tanks are not solving bottleneck limitations in the grid. Therefore, these two storage technologies exhibit different roles within the system.

2.3.5 Constraints of DSM

As the technologies introduced in the previous section presented flexibility constraints on the producer side, in this section examines restrictions on the demand side. DSM has many constraints which restrict the ease of utilization. Valor Partner’s (2015) report found several technical restrictions in DSM. Obstacles can be also found in the building structure, pricing contracts, and overlapping control devices. Economical restrictions are related with investment decisions, revenue allocation, and lack of regulation.

Since most DHC networks operate independently and on a small scale, applying DSM with the same algorithm will only shift peak loads in time. This occurs for instance by setting a load reduction requirement based on a schedule. Moreover, as energy is provided by pipes with restricted capacity, local bottlenecks may occur within the network. Another restriction is the timely inflexibility of DHC. The production processes of power plants are scheduled in advance, and energy needs to be produced well before the consumer’s actual need arises (Valor Partners 2015). Another obstacle can be found in the slow thermal renovation cycle of buildings. By increasing insulation and reducing leakage air rates, energy efficiency actions, such as setbacks and DSM are able to implement (Schmidt, Basciotti et al. 2013). The more buildings are able to participate in DSM actions, the more flexible the grid gets.

When considering predictive DSM and load control in buildings, there are certain constraints in the building’s components and radiator system, which do not allow audacious heating power increase or decrease. Table 3 recapitulates major technological restrictions.

Table 3: Factors which affect DSM and load control. Adapted from (Kekkonen 1988, Ahlstedt, Koskelainen 1995)

Charging constraints	**Discharging constraints**
Design temperature in the area	Heat capacity of building envelope
Maximal input temperature of 90 ˚C	Minimal input temperature of 75 ˚C
Radiator efficiency	Safety constraint
Maximum indoor temperature	Minimum indoor temperature

The design temperature leads to a restriction in DSM: with outside temperatures colder than the design temperature the radiators are on full power and therefore storing heat into the buildings is not possible. Another restriction is the maximal allowed input temperature of 90 ˚C (Kekkonen 1988). On the other hand, supply temperature cannot decrease because of DHW quality demand. Also, the inside temperature is inadvisable to cool down more than a certain amount in order to prevent moisture formation (Kekkonen 1988). Supply and demand elasticity can provide opportunities to develop DHC towards a more flexible operational environment. When in the past load control was implemented with individual adjustments, novel technologies are bringing a broader perspective to optimize the total system. These optimized DHC systems are better understood as smart cities which are discussed in the following section.

2.3.6 Thermal Storage in Buildings

The chapter ends with a literature review on active and passive TES and justifies the utilization of passive TES for predictive DSM. In thermodynamics, heat is defined as thermal energy that transcends a system border. Therefore, it can be expressed as a flow quantity which cannot be stored. Only the related energy in form of heat transmitted energy can be stored. Thermal energy storage systems are differentiated by the physical storage principle as well as by the time horizon of the storage. (Schäfer, Grote 2012). TES systems are classified as either a short-term storage, i.e. buffer storage, or a long-term thermal storage, i.e. seasonal storage. Buffer storage are utilized for time periods from an hour up to one week while seasonal storage is utilized for a time horizon that can be up to one year (Heier 2013).

A major advantage in DHC is the variety of possible techniques to store heat. Commercial TES techniques are based on either sensible or latent heat storage. Thermochemical heat storage, which are based on a chemical reaction of mediums which stores and releases energy much more effectively than water, are researched. Sensible heat storage systems store thermal energy by a change in the temperature of the material. The sensible heat storing technique which is of interest in this study has been found to be an inexpensive way avoid short-term peak loads (Kensby, Trüschel et al. 2015). This technique comprises either separate hot water tanks or the thermal inertia of the building envelopes to store heating energy. Thermal inertia is defined as the resistance against changing temperature (Heier 2013). The amount of energy that can be stored per change of temperature and per mass can be measured with the storage specific heat storage capacity (Henze, Krarti 2003).

Sensible TES in buildings can be divided into two techniques as presented in Heier (2013): passive and active energy storage. Passive systems retain heat in the building components within the active layer as discussed in the previous paragraph. Active storage techniques in turn aim to retain energy in buildings actively, i.e. with a deliberate energy input, such as electricity, pumps or fans. The main difference between a passive and an active system is that in the first one, uses temperature differences over time in the building for storing and releasing heat while the latter one, the components of the building are activated through embedded pipes (Heier, 2013).

Gadd and Werner (2013a) investigated heat load variation in DHC systems, as described in Section 2.2.5. They concluded that short-term TES should be of the size of 17% of the average daily heat supplied in the specific heating network in order to mitigate daily variations. A study by Kensby (2015) investigated how the indoor climate is affected if the district heating system feeds more heat to the radiator system before peak load times and decreases heat supply at peak load times. The results show that it is possible to store 0.1 kWh/m^2 in a heavy mass building without the indoor temperature varying by more than 0.5°C. In a Finnish simulation peak loads were reduced by storing 0.4 kWh/m^2 in a heavy mass residential building without affecting the indoor temperature by more than 1˚C (Jokinen 2013). Jokinen's simulation indicates that buildings built between 1940 and 2000 were most applicable for DSM, since they had large heat demand but were insulated well enough to keep the heat over the DSM period. However, both of the studies performed load control with a scheduled time. More dynamic approaches are found in the following chapters.

Schmidt et al. (2013) simulated load shifting actions in buildings with night time setback in a DH network in Austria. These buildings differed in construction and insulation. The simulation shifted the starting time of some buildings after the night setback. The sensitivity analysis of the study states that buildings which can be heated up fast are better suitable for DSM than heavy mass buildings. Heavy mass buildings could not reach a sufficient inside temperature if the heating was started later. The overall energy consumption of the area rose by 2.5%. Johansson and Wernstedt (2010) argue that energy savings in relation to heat load reductions can be achieved if the control system is able to handle the transition smoothly from reduction to normal operation. Similar results are also presented in Fourdeg's former study (Salama 2014).

The review of literature in this chapter has concentrated largely on empirical observations of DSM. Certain important concepts, such as data analytics, open heat market, and dynamic pricing, have been introduced to outline their importance for operating DSM. Thus, this chapter provides the framework for the next in which heating storage is outlined, and the data for the simulation is presented.

3 Modelling the Demand Side

In order to understand the technical conditions storing heat load storage in buildings, a specification of thermodynamic equations is presented. Additionally, building stock characteristics and individual space heating are discussed in order to understand the basics of the DSM tool discussed in the upcoming section. After this, thermal comfort of consumers is defined and an approach for valuing sufficient inside temperature is given. At last, provided heat load and temperature data is presented which enable the creation of the simulation model.

Passive storage systems are investigated in this thesis since the target is to simulate the influence of DSM on a realistic building stock. These buildings retain also a high thermal mass, and for their high share in the existing building stock they are practical to extend for large scale applications. In addition, Finland's buildings stock regenerates slowly and therefore, proposing a predictive DSM solution with a small investment appears reasonable. The thesis simulates heavy mass buildings because they possess a large thermal inertia. Heavy mass buildings are typically constructed with a core of concrete (D5 Suomen rakentamismääräyskokoelma, 2012), and they store energy linearly to increasing or decreasing temperatures (Heier 2013). Compared to light buildings which are constructed with a wood or steel core, researchers have found advantages in heavy mass buildings for load management (Henze et al., 2005, Kensby 2015). Concrete constructions reduce the surface temperature variations of internal walls. On the other hand, since energy is stored by variations in inside temperature, occupants need to accept temperature variations over the day (Heier 2013).

Heier (2013) states that the own mass of the buildings provides storage capacity in the floor, walls, ceiling, and in the water of the radiation system. This means that the sensible storage mediums are heated with the indoor temperature. Therefore, the larger the temperature variation is, the larger is also the potential for passive heat storage. In addition to sensible heat storage, the ceilings of buildings can be also equipped with latent of phase changing materials which have been proven to increase the storage capacity of buildings with less affect to the indoor temperature (Heier, 2013). Even though these building materials could enhance DSM capacity, the thesis focuses on existing concrete buildings.

3.1 Heat Transfer

As described by Ljung and Glad (1994, pp. 297-332), a model is called a stochastic model if the input factors contain randomness and probabilities. The model can be seen as deterministic if it has no contingency, i.e. with the same input factors and algorithm the output should be always the same. This thesis contains stochastic models. If a model presents a change in time, it can be either continuous or discrete. In a continuous model, input and output factors are fed as a permanent function of time, whereas in a discrete model factors are read within certain time points. A continuous model can be either dynamic or static. A static model needs only the input vectors of the conclusive time point, whereas a dynamic model is influenced also by former input factors and state values. For that former heating decisions are affecting the current decision of the heating device, a dynamic model is needed.

The following section describes the TES behaviour of buildings. The examples are calculated with heavy mass concrete buildings from the period 1980-1990. The building storage capacity and insulation determines how quickly the temperature adjusts to a change of the outdoor temperature which are put into relation through the time constant. The time constants determined by shutting down the energy system during a certain time to measure the temperature decrease and therefore can be seen as an approximation of the thermal inertia of a building (Wernstedt, Davidsson et al. 2007, Karlsson 2012) although it is for heat load control in short-term charging and discharging actions. The time constant τ is given by (D3 Suomen rakentamismääräyskokoelma 2012):

$$\tau = \frac{C}{H}, \tag{3}$$

where

H is the thermal conductivity [W/mK].

The thermal conductivity is the sum of various heat transfer coefficients in the building and their area (D3 Suomen rakentamismääräyskokoelma 2012):

$$H = \sum UA \tag{4}$$

By this the temperature change is given by (Osterlind, 1982):

$$\frac{T_{ae}(t) - T_{out}}{T_0 - T_{out}} = e^{\frac{-t}{\tau}}, \tag{5}$$

where

$T_{ae}(t)$ is the room temperature at time t,

T_0 is the initial temperature, and

T_{out} is the outdoor temperature.

Figure 10 shows the inside temperature change in a building with a time constant τ of 120h.

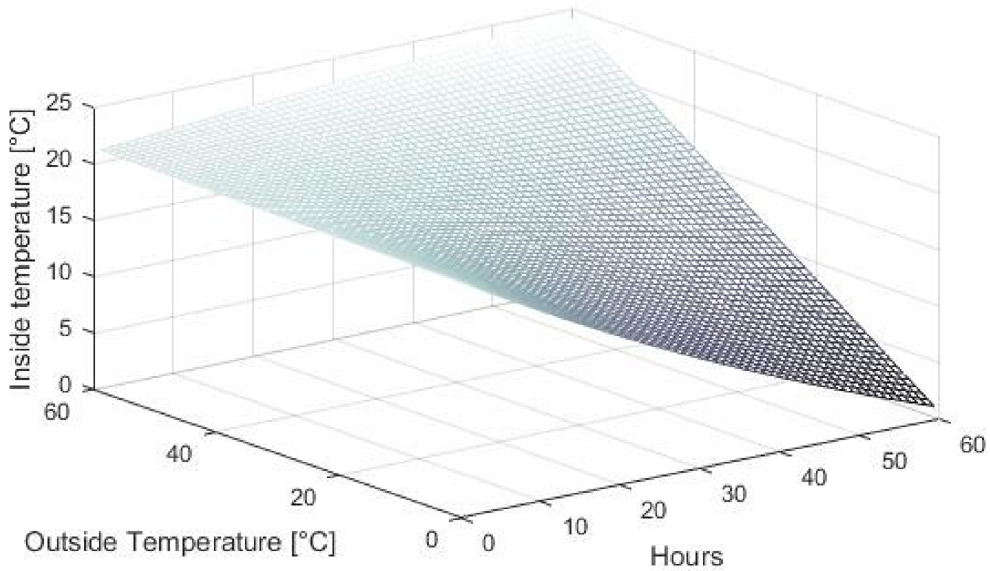

Figure 10: Example of the inside temperature change with a time constant of 120h.

As reported by Seppänen (2001, pp. 17-18), the reference temperature is better assessed by computing the operative temperature than only the indoor temperature. This is calculated by the average of inside temperature and the radiant temperature of an enclosure. The operative temperature reflects the effect of surfaces which temperature deviates from the surroundings and influence the thermal sensation of the inhabitants. The operative temperature is calculated with the standard SFS-EN ISO 7726:

$$t_0 = \frac{h_c \times T_{in} + h_r \times t_r}{h_c + h_r}, \quad (6)$$

where

h_c is the heat transfer coefficient by convection [W/m^{2}K],

h_r the heat transfer coefficient by radiation [W/m^{2}K],

t_r the mean radiant temperature [˚C], and

t_0 is the operative temperature [˚C] the is utilized further as the reference temperature.

The operative temperature can vary significantly of the inside temperature for example in rooms which have large windows.

SFS-EN ISO 13790 describes the thermal performance of buildings. There are many methods to calculate the heating time, such as quasi-steady state methods, which calculate the heat balance over long time periods, and dynamic methods, which calculate the heat balances with short time periods and taking account the stored and released energy from the mass of the buildings.

The dynamic method models thermal resistances, heat capacities as well as internal and solar heat gains in the building. This model is needed to compute temperature differences, and control the short-term loads of the building for energy and cost efficiency targets. A dynamic approach in calculations is also more realistic: the temperature and energy flow changes constantly depending on the external variables. The energy balance and the dynamic thermal model are shown in Figure 11. Such heat load balance models are the prevalent method of describing the thermal dynamics of building structures.

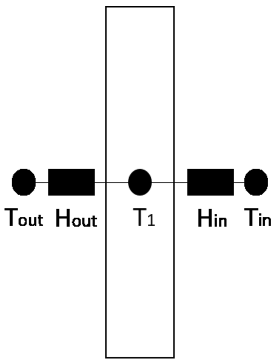

Figure 11: Building component and the dynamic thermal model (Siren 2015).

In awareness of the approximations in the model, the heat dynamics can be expressed as a differential equation. These models can be made sufficiently complex and might include several more variables than just one indoor temperature and one building structure temperature. The building model for this thesis is provided by Fourdeg and computed with the programming language Python and the numerical computing environment Matlab (Salama 2014). Precise descriptions of the differential equations are found in the literature (Andersen, Madsen et al. 2000, Siren 2015). The stored heat can be described as the difference of heat fluxes Φ:

$$\frac{d(stored\ heat)}{dt} = \sum \Phi_{in} - \sum \Phi_{out}, \quad (7)$$

which results as an energy balance equation (Siren 2015):

$$C \times \frac{dT_1}{dt} = \sum H_{out}(T_{out} - T_1) + \sum H_{in}(T_{in} - T_1), \quad (8)$$

where

C is the heat capacity [J/K],

T_1 the temperature of the knot [°C], and

H the thermal conductivity [W/mK], as calculated in Equation 4.

The left side represents the stored and released heating power while the right side represents the received and released heating flow. The differential equation can be calculated easily with analytical methods (Siren 2015). The following table presents an example of a room about the size of A=12m^2 with the same starting values as is Figure 10 computed.

Table 4: Temperatures and heat fluxes as a function of time in a typical 1980 building used in the study.

t [h]	Tout [°C]	Tin [°C]	T_1 [°C]	Φin [W]	Φout [W]	C*dT/dt [Wh]
0	5.6	21	10	320.7	-307.69	13.01
0.5	5.6	21	10.02	320.09	-309.16	10.93
1	5.6	21	10.04	319.47	-310.63	8.84
1.5	5.6	21	10.06	318.86	-312.11	6.75
2	5.6	21	10.08	318.24	-313.59	4.66
2.5	5.6	21	10.11	317.63	-315.07	2.56
3	5.6	21	10.13	317.01	-316.55	0.46
3.5	5.6	21	10.15	316.39	-318.03	-1.64
4	5.6	21	10.17	315.77	-319.52	-3.75
4.5	5.6	21	10.19	315.15	-321.01	-5.86
5	5.6	21	10.21	314.52	-322.5	-7.98

As seen in the table, the temperature at the knot heats up but it is delayed in time. The stored heat capacity changes from charging to discharging in proportion as a function of time. This table was conducted with a static first solution for T_1. However, as analytical approaches cannot be utilized in more complicated cases, a numerical method should be utilized. Since the thermal energy is stored in the building envelope, differential equations for both indoor air and components are needed. These are called two-time-constant heat balance models as described in Seppänen (2001, pp. 107-109). The convection part is calculated in the room air balance equation with the heat capacity C_a for air, whereas the radiation part is calculated in the envelope equation with the heat capacity C_e for each component unit. The latter heat capacity depends on the time gradient and the material of the component unit (Seppänen 2001):

$$C_e = \delta \times c_e \times \rho \times A_e, \quad (9)$$

where

δ is the active thickness [m]of the elements,

c_e is the specific heat capacity [J/K],

ρ is the density [kg/m^3] of building elements, and

A_e is the heated area [m^3] of the elements.

The active thickness is calculated as follows (Seppänen 2001):

$$\delta = \sqrt{a \times t}, \tag{10}$$

where

a is the thermal conductivity [m^2/s], and

t is the time length [s].

The active heat capacity of the building components can vary between 0.6-3 MJ/K[4] depending on the used materials and building structure and it can be at the most 100 times greater than the heat capacity of the room air (Seppänen 2001). Because of the time dependency, building elements might need several hours to settle to their new stationary state.

If the inner functions of the model can be neglected or if the determination of the above mentioned values is too difficult, a black-box model can be formulated. These models find advantages in real systems with measured data, since they determine the correlation between input and output factors (Ljung, Glad 1994). This model can be utilized, especially if exact building data are not provided. Further description of the black box model and energy demand prediction is presented in 4.3.

3.2 Consumer Behaviour

While the physical aspect of building energy storage is investigated, it is concluded that passive TES influences the inside temperature of the building. Therefore, the social aspect of consumer comfort in relation to energy conservation and control measures stands continuously out. As presented in Table 1, the consumer, or end user, is seen as a central subject in DSM. On the other hand, as consumers are not necessarily directly in charge of heating decisions, the requests may be presented from the customer, i.e. decision-maker. This stakeholder can be for example the real estate possessor, building commission, or the administration of the building is outsourced to third party operators. For targeting the optimal indoor temperature, the thermal comfort of the inhabitant needs to be closely investigated.

3.2.1 Thermal Perception

Thermal comfort is strongly related to the thermal balance of the body, which itself is influenced by environmental and personal parameters. Environmental parameters count air temperature, mean radiant temperature, relative air velocity, and relative humidity. Personal parameters are activity level, and thermal resistance of clothing as described in Hensen (1991). Thermal comfort is strongly related to the thermal balance of the body, which itself is influenced by environmental and personal parameters. The environmental parameters were air temperature, radiant temperature, air velocity, humidity, clothing and activity. Personal parameters were activity level or metabolic rate, and thermal resistance of clothing. Tuomaala (2013) states as well that individual characteristics have an impact to the thermal perception. These factors are for instance age, gender, and tone index

[4] These are estimated for office and residential buildings (Seppänen 2001, pp. 109).

values. These are most likely due to individual body fat and muscle tissue ratios (Tuomaala 2013).

The most commonly accepted method to estimate the significance of these parameters is provided by Fanger's (1972) comfort equation and his practical concept on Predicted Mean Vote (PMV). This traditional computation method appraises the thermal perception and comfort. The PMV method is based on a heat balance model where the test persons' response on six variables: air temperature, mean radiant temperature, air velocity, air humidity, clothing resistance, and activity level (Olesen 1982). However, the PMV method progressively over-estimates the mean perceived temperature in warmer or cooler environments and is therefore only valid under certain conditions (Holopainen 2012). As an example, when commuting from a cooler region to a warmer one, the body is stressed and sweaty, but after a few days it is used to the changed environmental conditions.

3.2.2 Work Performance

Satisfaction with the thermal environment is important for its own sake and because it influences productivity and health. The literature contains various office field studies which were arranged in call centres; in these studies, the speed of work, which is measured by the average time per call, represented work performance. Laboratory studies typically assessed work performance by evaluating the speed and accuracy with which subjects completed tasks, such as text processing and simple calculations. The studies were regression weighted by sample size and relevance. As a result, office workers who are satisfied with their thermal environment have been found to be more productive (Hongisto, 2005).

Seppänen et al. (2006) collected various studies which compared work performance with indoor temperature. The studies were regression weighted by sample size and relevance as seen in Figure 12.

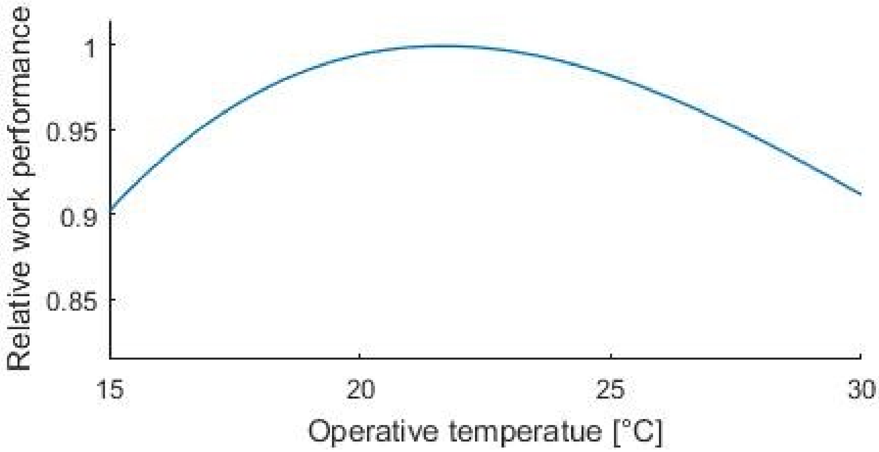

Figure 12: Normalized office work performance in relation to temperature (Seppänen, Wargocki et al. 2006).

The outcome is a concave function with the maximum point of relative performance at T=21.75˚C. The fitted equation provided by the authors is used in the simulation of marginal cost for the consumer which will be further described in Section 4.5.2.

Approaches on measuring work performance are debated actively. Holopainen (2012) claims that the thermal comfort estimation should additionally take into account the natural tendency of people to adapt to changing conditions in a dynamic building simulation environment by means of the human thermoregulation system. The thermoregulation system predicts the thermal behaviour of the human body as well in steady-state and in transient indoor environmental conditions. Furthermore, because thermal perception varies on individual fitness, gender, and age, indoor temperature variation and thus passive TES realization should be highly individual (Tuomaala, Holopainen et al. 2013). This can be achieved by adjusting the reference temperature of the room towards to its own comfort zone.

However, everyone does not have the luxury to adjust the indoor temperature, for instance from a public room to one's own need. Therefore, a more general tolerance level should be distinguished. Holopainen's study defines boundary conditions such as surface temperatures and radiation heat transfer in the building simulation environment. These boundary conditions for a suitable thermal comfort by studying the effects of various internal and external parameters on human thermal perception. The simulation results indicate that the operative temperature, metabolic rate and clothing are the most dominant boundary conditions for the human thermal sensation and comfort.

Measuring the thermal perception of inhabitants has multiple interesting gains. One purpose is to estimate the connection between saving energy and consumer comfort. The next section examines former studies on modelling consumer perception for both cold and hot climates.

3.2.3 Significance on Heating

Henze et al. (2005) model a penalty system for adjusting the indoor temperature out of the comfort zone. It takes also in consideration the inhabitants' occupancy. In his study, the cost of thermal comfort is calculated with PMV (Fanger 1970). Also Heier (2013) developed a method in which the total costs of consuming DHC are the total costs for heating multiplied with a thermal comfort penalty. It describes penalty with Fanger's PMV model as an increasing gradient in a parabolic function. Mozer et al. (1997) qualify the marginal cost as a function of the average wage of office workers. To estimate the value of discomfort, the controller claims for the weighting values for work performance. By this, a company, or customers in general, can individually rate the value for DSM.

Wargocki et al. (2006) report that staff costs are approximately 100 to 200 times the cost of energy and 20 to 44 times the cost of ventilation costs in offices. Thus, a relative small increase of productivity will constitute superior economic gain than a decrease in the energy bill. According to the ASHRAE Standard 55, 80% of sedentary or slightly active persons find the environment thermally acceptable. Holopainen (2012) states that thermal sensation and comfort relates in addition to operative temperature also to the metabolic rate. Hence, the inhabitant can adapt to changing indoor temperature better than in previous studies stated. As the objective of this study is not to label how customers should value the thermal sensation of end users, the model accounts the marginal cost for consumers as a function of thermal dissipation and weighting factor for consumer comfort.

3.3 Collected Data

In order to simulate as realistically as possible, real heat load data is provided by Helen, the DHC producer for the city of Helsinki. The data are hourly measured heat loads from 12 heavy mass buildings in Helsinki during the year 2015. Smaller premises, such as detached houses and terraced houses, are not investigated. The buildings are expected to be situated in the same district, which decreases errors in DH transmission. In addition, all buildings are constructed in the same period of time (1980-1990), ergo space heating losses and ventilation losses can be approximated to behave in the same manner. The buildings were constructed in a time when many urban districts were built in Helsinki (City of Helsinki 2006). Additionally, first large scale energy efficiency actions were performed during this period (Pesola, Vehviläinen et al. 2011). Since the data include the total energy amount of the building units, the heating amount targeted for ventilation and DHW is decreased with approximations as described in Chapter 3. Figure 13 shows the total heating load of the system and the contemporary outside temperature.

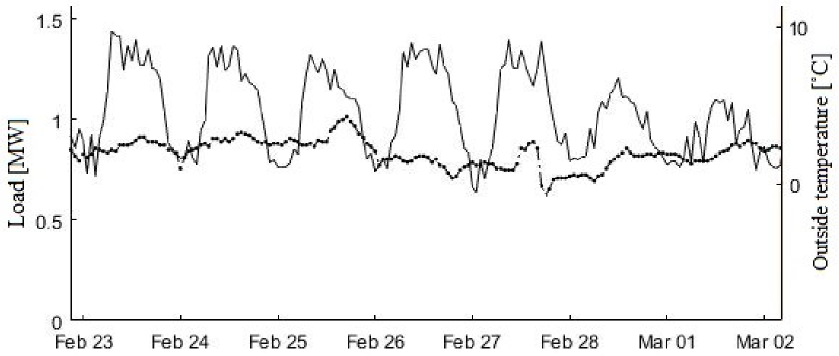

Figure 13: DH load profile of the given dataset during one week with steady outdoor temperatures.

Buildings can be divided by the construction classification of the Finnish statistical centre (Tilastokeskus 1994). From this classification, buildings are further lumped together depending on behavioural patterns resulting in four clusters: residential, office, commercial, and industrial. Studies on DSM, both in DHC and electricity systems, have divided the buildings to similar clusters (Pavlak, Henze et al. 2014). The buildings in the model are seen as small, decentralized storage capacities which are optimized in a VPP concept. VPPs utilize the segmentation of the customers to provide the producer enhanced forecasts and analytical information about the value these particular customers (Zurborg 2010). Figure 14 presents floor space distribution of building types connected to a DH network. It shows that most of them are residential buildings.

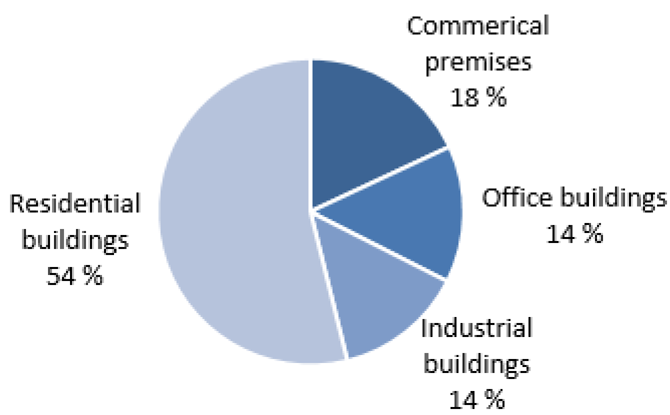

Figure 14: Floor space distribution of DH connected buildings in Finland.. (Statistics Finland 2009)

The main justification for this clustering approach is based on occupancy time and prediction reliability. Residential buildings include apartment blocks, terraced houses, and single-family houses. The latter two possess a majority in connection numbers, but a minority in delivered heat volume. The office buildings cluster contains office buildings, public buildings, and educational buildings. Commercial premises include additionally the care industry and traffic buildings. At last, the industrial buildings cluster includes industrial buildings and storage buildings. Further clusters, including public buildings, swimming halls, hotels, and sport halls, could have been divided. Even though all of these have special features which affect the heating load, the simulation separates buildings only by occupancy status and reference temperatures. Therefore, these four clusters provide a sufficient approximation.

In contrary to space heating, DHW demand is constant over the season. The share of consumed hot tap water varies notably between building types. While DHW in residential buildings takes roughly 25% of the total heating energy consumed, the hot tap water consumption of office buildings, public buildings, and educational buildings can be nearly neglected (Koskelainen, Saarela et al. 2006). Table 5 presents the amount of heating energy allocated to DHW heating according to Finnish construction regulations.

Table 5: Share of DHW usage in different buildings (D5 Suomen rakentamismääräyskokoelma 2012).

Building cluster	**DHW energy [kWh/m^{2}a]**	**Average share of total energy consumption**[5]
Residential building	35	28%
Office building	6	5%
Commercial premise	4	3%
Industrial building	6	5%

The outside temperature data for the city of Helsinki is provided by the Finnish Meteorological Institute for 2015 (Finnish Meteorological Institute 2015). Another approach would be to retrieve temperature data from 2012 which would be the test year for building energy demand (Jylhä, Kalamees et al. 2012-05-01), the accurate heat load dataset from the year 2015 determined the utilization of outside temperature data from the same year.

This chapter introduced the main computational theories on storing thermal energy within the thermal inertial of buildings. To quantify storage load factor and inside temperature, it is necessary to have a model. As the is described by complex differential equations, a black-box concept has been introduced in order to optimize buildings of different type without having accurate data. In practical use, simple empirical correlations can be distinguished in order to shorten the computation time and increasing accuracy. Basics on consumer comfort and device configurations are also presented. This information provides the framework for the development of a predictive DSM model which will be described in the upcoming chapter.

[5] The average share is computed by assuming a heat index of 125 kWh/m^{2}a (Finnish Energy 2016a).

4 Model Description

Previous studies on DSM targeted to reduce peak loads and thereby smoothening consumption variation based on a scheduled controller in the building substations. However, as the peak hour of a building is not necessary during the peak hour of the DHC system, a more effective strategy for DSM would be to control loads based on market signals. Furthermore, as high loads do not automatically mean high production prices, DHC market signals include also factors on electricity prices, former investment decisions, and dynamic grid load. While DSM is discussed until this section in both district heating and district cooling systems, the simulation puts into practice in heating systems.

This chapter describes the method of practical implementation of predictive DSM. Firstly, the method of the predictive control device is described. The following part continues with the formation of the marginal cost for the consumer by setting an objective function with boundary conditions of thermal perception, work performance, and heat losses as described in Section 3.2.

The controller receives a changing price for DH in order to control the building based on the actual load of the system. For this reason, price signals need to be constructed. First, Section 4.6 investigates the forecast of heat demand. Forecasting tools and control decision methods are described in order to understand the importance of the iterative features in the DSM controller. In the following section, the impact of diverse factors in DH demand forecasting is discussed. These are utilized for quantifying the amount of shifting loads due to DSM.

From this information, Section 4.7 describes how a typical DH system can be modelled. The next section discusses price formation and merit order of power plants. These factors allow a simulated DH system to be modelled that can use a typical Finnish fuel mix. The model is created to simulate an hourly price for DH. This hourly price is then utilized to give price signals to the buildings equipped with a predictive DSM controller. In addition, the model presents both the cost structure for DHC generation as well as potential cost saving factors using DSM from the producer’s perspective. It should be noted that the purpose of this pricing model is to simulate the realistic volatility of DH tariffs for the network. Hence, the calculations should be seen as suggestive.

The last part focuses on how various buildings can interactively fulfill the need for short-term load shifting. This is done by merging the requirements of producers and customers to an agent-based auction platform which optimizes load on system level. The platform communicates with the producer agent and the consumer agents and takes action when a DSM event occurs. A DSM event, similar to DSM action, can be described as a time-constricted target of either filling off-peak loads or shred on-peak loads. By implementing independently acting accents and separate events, the risks of shifting peak loads from one hour to another, and other risks, can be mitigated.

4.1 Predictive Controller

The inner functions of the heat load controller in the simulated rooms studied are described in this section. Inner functions include the features of the decision making, forecasting, room structure, and verification tools. The decision making process of the controller can be described with the schematic presented in Figure 15. The predictor receives internal data from the monitoring device, such as the environmental state of the room. The user has settled occupancy and boundary conditions for the controller. These boundary conditions include maximum and minimum temperatures at all occupancy states and the consumer's willingness to participate on energy control. Realized consumption data are available from the database as well as information about the neighbouring rooms. Additionally, the predictor receives external input parameters, such as weather forecasts from the Meteorological Institute and price signals from the DH company.

The conditions for a DSM event depend on the ability to store heat in the building and on the heat losses. Therefore, the first parameter is the heat loss as a linear function of the ambient temperature depending thermal resistivity of the building. The other parameters are nonlinear heat gains through solar loading, machine operation, and human traffic. After receiving the input data, predicting the consumption, and making a conclusion, the regulator processes the controller's output and matches it to a temperature thermostat set-point which is selected from Appendix 1 of assigned set-points to different energy ranges. Simultaneously, the controller monitors the temperature change and sends new input to the controller.

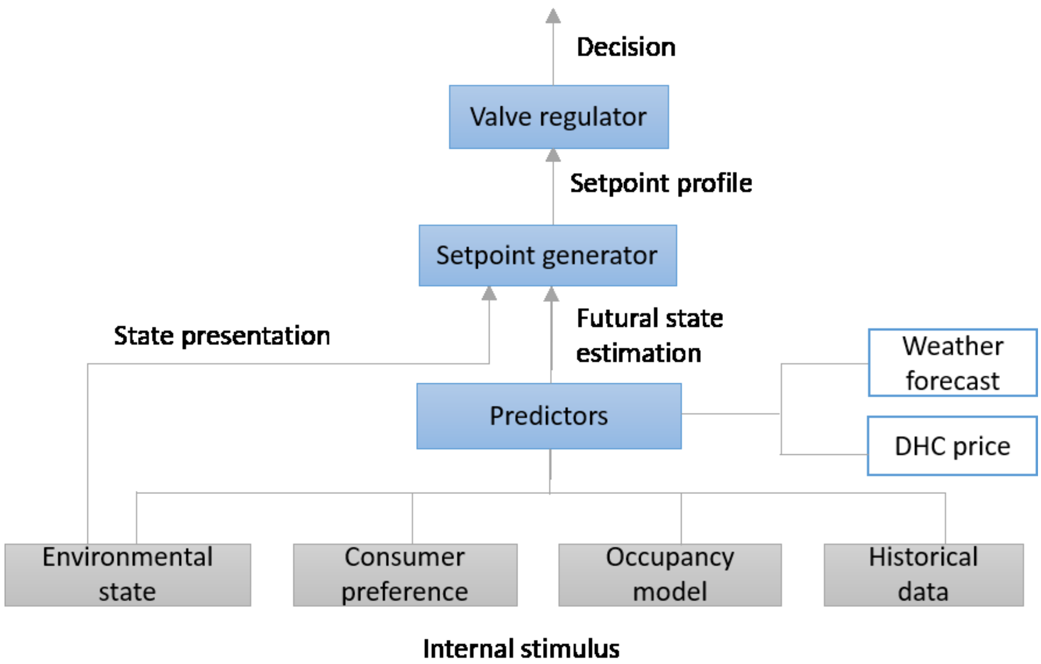

Figure 15: Schematic presentation of the regulator created for this thesis.

The future state of the controller is estimated with model predictive controls (MPC). The data is validated in an artificial neural network (ANN) prediction model. These advanced computation methods are further described in the following sections.

4.2 Model Predictive Control

As studies by Kärkkäinen et al. (2003) indicate, a successful load control strategy comprises a stepwise change of the reference temperature. The researchers argue that heat supply should not be switched completely off during a DSM event even though the thermal capacity of the buildings would allow it, since strong load reductions can cause higher recovery loads than the initial maximum demand was. However, in a complex system momentarily higher heat loads in building units do not necessarily affect negatively the system. In order to predict the consequences of controller decisions, an MPC method is introduced in the upcoming section.

MPC solutions for passive TES has been investigated especially in electrical cooling applications. Henze (2003) studied on controllers which post-processed an optimal strategy in order to get a control command for the current controller decision. The controller could either minimize electrical energy consumption or electricity cost. If the aim is to reduce energy consumption, the authors state that a passive building TES is not required. On the other hand, if using cost optimal control, thermal storage inventories should be utilized. The controller predicts the required set-point temperature depending on the utility rate structure, occupancy, and peak price duration.

Figure 16 presents the procedure of the MPC as described in the work of Henze et al. (2005). As the time controller could continue infinitely in time, a predefined prediction horizon is created and of the generated optimal strategy only the first action at stage *t** is executed. The time horizon can be set at various times, perceiving computation time. The MPC algorithm is designed to forecast every 10 minutes the building state and make decisions based on the data. The time window is shifted over *t* time steps forward and the forecast is updated at each time step. By this, the predicted profile shifts from the initial forecast profile to the optimal profile, which are illustrated as dotted and dashed lines, respectively.

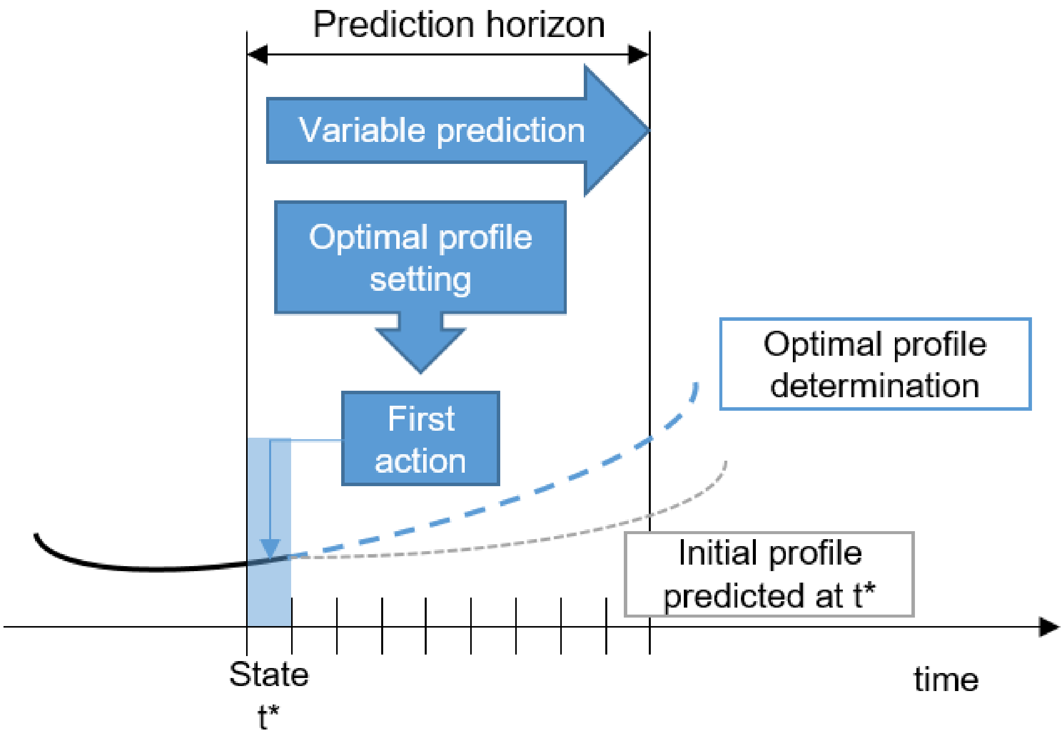

Figure 16: Predictive optimal controll of the load profile. Adapted from (Henze, Kalz et al. 2005).

4.3 Artificial Neural Network

The next step is to consume heating energy when it is lucrative with DSM. The heating demand is controlled by a machine learning algorithm which adjusts the inside air temperature to a comfortable level in case of occupancy and optimizes energy consumption when the room is empty. Each room is managed separately and the building is connected to a DHC network. Additionally, it collects data from the building and provides alarm service for maintenance. Furthermore, intelligent programs predict also building characteristics and inhabitants' activities in the buildings, such as open windows and occupancy. Statistical regularities in inhabitant behaviour can be exploited to save energy. For instance, occupancy patterns are predicted with a calendar factor. More sophisticated occupancy predictions could be implemented with GPS signals or CO_2 sensors (Gupta, Intille et al. 2009, Fabi, Camisassi et al. 2015). In addition, the controller learns the thermal characteristic of a building with artificial energy and temperature data (Mozer, Vidmar et al. 1997).

Since the consequences of control decisions are delayed in time, the controller needs to anticipate energy demand with predictive models based on statistical regularities and advanced forecasting tools. These algorithms include regression models, time-series models, Kalman filters, and ANN algorithms. Utilizing ANN for short-term DH forecasting have been tested in this thesis in order to understand the importance of input factors in the simulation. The concept of ANN is described in Eriksson (2012) and presented in Figure 17. The basic idea is to divide a complex problem into simple elements, i.e. nodes. These nodes are multiplied by weights and then computed by functions which determine the activation of the neuron. Another function computes the output of the artificial neuron. ANNs combine artificial neurons in order to process information. The main advantage is that they enable to capture nonlinear data, i.e. discontinuous functions, which is often the case in DH demand. ANNs can be viewed as black boxes. As black boxes receive on the first hand input and output factors, it needs an additional layer to compute the relationships between input and output factors. This is why ANNs have additional hidden layers to mathematically approximate any relationships between input and output.

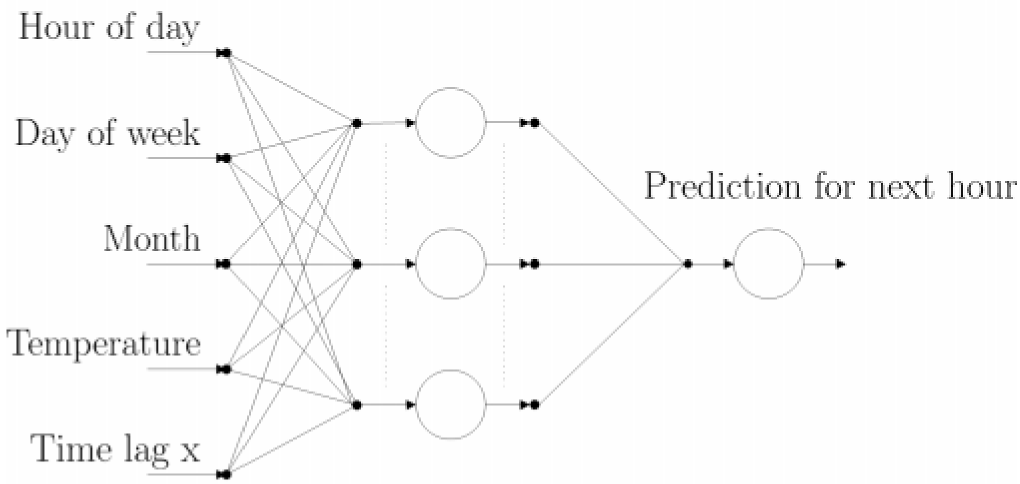

Figure 17: ANN network for load prediction (Eriksson 2012).

Since the building energy control deals with conflicting issues for optimization, such as minimum energy consumption, minimum cost function, and the maximum comfort, the task could be realized with a mixed integer linear problem (MILP). Studies with single objective functions optimize for example only the cost function and therefore neglect comfort maximization. The two individual requirements are merged in a cost function such as (Mozer, Vidmar et al. 1997):

$$J = \lim_{k \to \infty} \frac{1}{k} \sum_{t=t_0+1}^{t_0+k} e(u_t) + m(x_t), \tag{11}$$

where

t is the time,

t_0 is the initial time,

u_t is the control decision,

$e(u_t)$ is the energy cost related with the control decision of u_t,

x_t is the environmental state, i.e. operational temperature in the room, and

$m(x_t)$ describes the marginal cost for the customer at state x_t.

In addition to this cost function, a DH price factor is introduced. The target of predictive DSM is to minimize energy consumption not only when it is possible, but when it is cost efficient. The optimal solution can be found on a Pareto frontier where neither of the two objectives can improve without deteriorating the other objective (Belegundu, Chandrupatla 2011). This approach is further discussed within penalty functions in Section 4.5.

The complexity and size of the problem may affect the solution time when applying an optimization method. Therefore, as much data as possible should be fed to the model before it is trained. The data include factors discussed in Chapter 3 and especially in Section 3.5. By these pieces of information, a starting value of sufficient accuracy is created and the controller adjusts temperatures progressively. Additionally, the cost of communication needs to be considered. The optimization algorithm assumes that computation and communication will occur as planned. However, in the case of communication failure, the controller is able to control the energy consumption of a building with its initial data by utilizing fuzzy logic[6] (Salama 2014).

4.4 Room Characteristics

Each room and each building react differently on DSM. Some rooms and buildings are more resistant to participate in a DSM action. Jokinen (2013) determines that most critical rooms for load curtailment in residential buildings were upper level corner rooms since thermal dissipation has there the strongest effect. If DSM would be applied to the whole building depending on these rooms, it could not be extended to its full potential. Therefore, individual controllers are implemented to each radiator valve in order to optimize the room and participate independently in DSM events. A separate room model has been provided to simulate the effects of controlling a radiator heating system with a DSM feature.

The simulated building has three rooms as seen in Figure 18 with different wall and floor areas. The heat balance is created for every room and each room is divided into an indoor air control volume and several control areas for building components.

[6] The values of variables in a fuzzy logic are considered as truth values varying between 0 and 1 (Salama 2014).

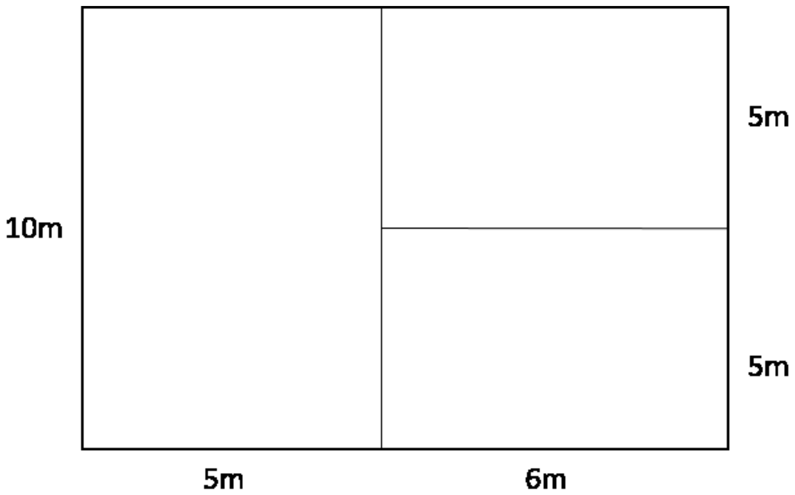

Figure 18: Simulated room model.

The occupancy status is presented as a binary number. In the case of occupancy, the inside temperature can vary within its limits set by the user. In the case of no occupancy, the MPC device optimizes the energy consumption and adjusts the inside temperature to the reference temperature before the room is occupied again. Since each thermostat valve acts individually, each room can be adjusted to DSM separately. By this, the full potential of the thermal capacity is utilized. With this approach, conductivity of the inner walls between rooms needs to be taken into account in the room model by setting different variables for each building component.

The model utilizes commonly accepted recommendations as boundary conditions. Appendix 1 presents a list of building usage, and recommended reference temperatures for most rooms in residential buildings and mean temperature for other building types. The full potential of DSM is enabled by taking individual preferences into account. For example, in residential buildings, the hallway and staircase can participate in DSM events first. After that, the living room can participate etc. until a sufficient amount of load is shifted or until the upper boundary of heat capacity is reached. The classification can be also more dynamic, i.e. when a window is opened, it gives a signal to the controller that the heating of the room is less important. The inhabitant can also decide whether to participate in the load management event completely of partial by an arbitrary value in the optimization (Abdulaal & Asfour 2016).

As described in Section 3.1, the heat capacity of air is small and thus changes in indoor temperatures are recognized faster. Seppänen (2001, pp. 16) claims that fast indoor temperature changes are felt as unpleasant, even at optimum average temperature, and therefore changes should be restricted to 1 °C. The air temperature should not vary more than 2 °C/h. Small intake air rates and low temperatures lead to condensation and inside damp. These give further constraints in addition to the reference temperatures as well as upper and lower bounds listed in Appendix 1.

4.4.1 Validation of the Model

Validation means the assurance that the data meets the required scope of the system[7]. Verification is the evaluation whether the data complies with a requirement, specification, or imposed condition. Table 6 lists constraints which the optimization program should meet.

Table 6: Verification conditions of the simulated room model. Adapted from (Schmidt, Basciotti et al. 2013).

Audit	Plausibility	Unit
Outside temperature	$-30 < T_{out} < 30$	˚C
Inside temperature	$15 < T_{in} < 30$	˚C
Cumulative energy consumption	$Q_{i+1} - Q_i \geq 0$	Wh
Power flow	$Pmax \geq \dot{Q} \geq 0$	W

The room model has been tested with various temperature ranges in order to adjust the weighting factors to sufficient accurate values. With these settlements, the marginal cost curves can be evaluated.

4.5 Marginal Cost for the Consumer

The following section describes the relation of marginal costs for the consumer of the control decision affected by the pluralist optimization characteristics discussed in Section 4.1. Marginal cost refers in this section to the value of what is given up in order to gain an additional unit. Here, the marginal cost is seen as the amount of energy which is abandoned at a certain hour in order to gain a monetary compensation. As the customer is responsible for the thermal comfort of the end user, thermal perception and the value for thermal comfort is discussed. Other costs for the customer are occurring by additional heat losses when energy is stored within the elements of the building.

Space heating losses, leakage air losses, and ventilation losses depend on the difference between inside and outside temperature (D3 Suomen rakentamismääräyskokoelma 2012). The sensible TES are charged by increasing indoor temperature and consequently causes larger thermal dissipation. The significance of the difference decrease by decreasing outdoor temperatures and thus can be formulated as a linear function. As this additional cost of energy is financed by the customer, it gives a simple measurement on the costs of DSM. At last, the controller creates a marginal cost for the consumer depending on the indoor temperature status, extraordinary heat losses, occupancy, and type of building usage.

4.5.1 Device Usage

When predicting consumer behaviour it is often presumed that consumers act rationally. However, small changes from the authority side can lead to large behavioural changes on the consumer side. In a recent study of user performance, Fabi et al. (2015) describe that optimization algorithms revoke initial consumer settings and diminish consumer's ability to control for example indoor climate. Consumers have found to be suspicious on the functionality of the algorithms and demand to have the power to adjust the settings to their current preference. Moreover, requiring users to explicitly provide feedback about

[7] Validation implies that the steps of the model building have to be critically scrutinized in order to find factors which needs to be dismissed or improved (Ljung, Glad 1994).

their actions has proved to be a very inefficient means of performing heating control because consumers do not have enough incentives to engage with the device (Gupta, Intille et al. 2009). Consequently, default settings might be left unchanged and learning algorithms based on explicit consumer feedback may execute unwanted actions. Therefore, the controller is set to learn automatically.

On the other hand, vigorous change in settings might lead to over-reactions within the building or system. Therefore, when predictive DSM devices are designed, they need to be both robust to provide system reliability and agile to serve the end user. To achieve user comfort, an arbitrary value is implemented which gives the user the capability to decide whether to participate in a DSM action and adjust the stage of contribution. However, it seems beneficial that the value is not changed after installation to secure system reliability. By having fixed user settings, the DSM aggregator can also predict the TES capacity of the building better.

When the customer requires heating in time services, or ToU services, concerns on privacy policy and data ownership emerge. Collected information relates to a consumer's energy profile in the context of their energy use and it is exploited to take decisions which are directly affecting that individual. Through careful design, occupancy patterns and heating data can be accessed with the customer's or consumer's permission, and by trusted actors via trusted channels (Lähteenoja 2016).

4.5.2 Penalty Function

Since thermal perception is the sense of temperature and therefore related to how consumers feel, it is challenging to define the cost of changing the indoor temperature physical or psychological terms (Hensen 1991). However, as the thermostat valve is designed to be interactive and thus settings are adjusted to the consumer preferences, suggestions provided by Seppänen (2001) for estimating consumer discomfort can be utilized.

As the MILP model described in Section 4.3 is not yet utilized, the weighting of different objectives is realized with a penalty function. In penalty functions, a sequence of unconstrained minimizations is developed as in Belegundu et al. (2011, pp. 261-269) explained. Simple algorithms can be used at each step but each unconstrained minimization can be a large hurdle unless the problem formation has a special feature, such as involving quadratic function. The room model can be simplified as a differential equation expressed as:

$$T_r(t+1) = A \times [T_{out}(t) - T_r(t)] + (1 - A) \times [T_{ref}(t) + \Delta T_{ref}(t)], \quad (12)$$

where

T_r is the temperature of the room [˚C] at the upcoming hour $t + 1$,

T_{out} is the outdoor temperature [˚C] at time t,

T_{ref} is the reference temperature [˚C] at time t,

A is an unknown parameter, which is primarily different in start-up than shutdown,

ΔT_{ref} is the correction term send from the room model.

The reference temperature can vary during the day, as other energy control strategies, such as night or day time setbacks, might be included. With an addition to the cost function J, the controller can take into account the changing expense by minimizing the quadratic cost function:

$$\sum_{t=1}^{n} J = \left[T_{ref} - T_r(t+1)\right]^2 \times B + \left[T_{ref}(t) + \Delta T_{ref}(t)\right] \times P(t) \\ + F \times \Delta T_{ref}(t)^2, \quad (13)$$

where

J is the sum over a predetermined measuring value n,

B is a weighting coefficient for consumer comfort,

P is the ratio of how expensive the given hour t is over the average hour, and

F is a weighting coefficient for air temperature change.

This ratio can be calculated as follows:

$$P(t) = \frac{V(t)}{\frac{\sum_{i=1}^{24} V}{24}}, \quad (14)$$

where

V is the actual price for energy delivered to the building [€/MWh] at hour t.

In this thesis, it is resulting from the simulation in Section 4.7. In later use, producers can set this value based on their plant driving pattern.

These equations are combined in order to design a quadratic programming problem[8]. As explained earlier in this section, penalty functions need to have sufficient boundary conditions. These could be for example the derivate of temperature change, i.e. maximal gradient, and boundaries for T_r. The starting value for parameter A is chosen based on room configurations as described in Section 3.6. The parameters B and F can be iterated for example by utilizing Seppänen's (2001) work performance equation as illustrated in Figure 12, or by setting individual parameters based on the request of the consumer. If a boundary condition is crossed, the initial term is corrected. From these equations, the controller is able to adjust the load in an intelligent manner, i.e. to raise load on an upcoming price peak. Similarly, the load can be dropped without surpassing temperature restrictions. Increasing load leads to a positive ΔT_{ref} and vice versa.

The cost of discomfort can be expressed with the first part of Equation 13. The square of the difference increases when T_r approaches constraints. By adding the cost of temperature change, the marginal cost for the consumer can be developed. The utilization of the cost function in order to quantify the ability of the room or building to participate in DSM is discussed in Section 4.8. In order to simulate the model in a realistic way, the next section discusses forecasting and out of this information, the marginal cost for the producer is formed.

[8] Quadratic programming refers to optimization problems where the objective function is quadratic and the constraints are linear. The quadratic objective function can be either convex, which makes it simple to solve, or non-convex, which makes it difficult to solve. (Belegundu, Chandrupatla 2011).

4.6 Demand Forecasting

Accurate demand prediction is reasonable from both the building perspective and the system perspective. First, the prediction of the demand of individual rooms and buildings gives the load controller required knowledge of the building actions. When buildings are connected to a DSM system, the initial forecast of the DHC consumption can be utilized as a baseline for measuring the participation of DSM in the system. By having the difference at each time spot, the operator can calculate the compensation for the DSM event which will be further discussed in Section 6.3.2. These forecasts of each building can be also communicated to the DH provider which in turn enhance its own calculation certainty.

Accuracy in the whole DHC system prediction is in turn the other important factor. If DSM events play a part of the balancing mechanism of the system, a precise prediction of the demand at each hour should be created. Errors can be costly in terms of unmet demand or obsolescent stock. Production planning for many domestic heating systems has been performed by using historical load profiles and weather forecasts in an attempt to predict future heat demand (Fang 2016). In the past, short-term load planning was based on two-dimensional contour plots showing historical power output as a function of time and outside temperature. The utilization of contour plots gives a moderate approximation of what the historical mean production has been but predictions could be much improved and simplified by using an automated system (Eriksson 2012). The thesis assumes that short-term price forecasts for DH are created by predicting DH demand for the next 24-hours and calculating the merit order of the power plants. A realization of this approach is demonstrated in Section 4.7.

Several methods for load prediction have been suggested and implemented. Most applications in the subject consider the prediction of electrical power loads. As stated in Section 2.3.3, differences between an electrical power grid and DH network should be taken into account when forecasting heat demand. However, due to the high number of similarities between the two load prediction types indicate that the same type of algorithms may be used (Dotzauer 2002).

The prediction has been tried out with Matlab's Neural Net Toolbox (MATLAB 2016). An ANN is taught by iteratively adjusting the weights until the correct result is produced. To secure modest calculation times, the number of iterations can be restricted (MATLAB 2016). The ANN toolbox received input data for ANN training from realized demand from 2015 and predicted the next 24-hour demand. However, the actual simulation of the thesis utilized realized data from Helen to mitigate computation errors.

4.6.1 Weather Impact

Space heat losses depend on outdoor weather conditions as reported in Section 3.1. The most significant one is the outside temperature. Studies in demand forecasting vary which secondary weather factor, such as wind speed, solar radiation, or relative humidity, effects on the average system demand the most (Dotzauer 2002, Henze, Kalz et al. 2005, Fumo 2014). The significance of the factors depends mostly on the geographical area of the DHC system. For example, Fang (2016) assumed that wind speed could be an important factor because higher wind speed creates higher air flow within various cracks in buildings which increase heating demand. Nevertheless, the regression analysis did not indicate a high dependency on wind. The Meteorological Institute appraises that solar radiation has the most impact of these secondary weather factors on buildings (Jylhä, Kalamees et al. 2012). Therefore, Figure 19 demonstrates the linear dependency of outdoor temperature and DH demand with a 24-hour centered moving average in the Helsinki region. The correlation can be clearly distinguished especially during spring and autumn. In summer, solar radiation and DHW consumption determine demand.

Figure 19: Total heat load data from the dataset (solid) and outside temperature data (dashed) as 24-hour centered moving average.

The accuracy of weather forecasting is continuously improving with increasing calculation capacity and developing measurement technique. The quality of weather forecasts has been found to be more important than developing advanced load prediction algorithms (Dotzauer 2002). According to the Finnish Meteorological Institute (2016), the outdoor temperature over the next 24 hours can be forecast with 90% accuracy and over the next 48 hours with 85% accuracy. Precipitation predictions are nearly as accurate as the temperature assessments. Predictions of high wind speed are also improving.

The simulation is created with weather data of Helsinki from the year 2015. This data is accessible from the Meteorological Institute's Open Data database (Finnish Meteorological Institute 2015). The simulated model utilizes outdoor temperature and humidity data. The latter one was selected as a secondary weather factor because of the presumption that the Southern coast of Finland has relatively high precipitation rates. However, the model counted a low dependency between humidity and DH demand for the trained and predicted sections.

4.6.2 Social Factor

The accuracy of forecasting depends also highly on the social component. The difference between weekday and weekend as well as midweek holidays affect clearly the amount of DHC demand (Fang 2016). Based on this information, the data were divided into working days and weekends. Midweek holidays were neglected even though they are simple to implement with a calendar factor. The significance of weekends and holidays depends on the composition of the building stock in the network: as residential buildings consumption is steadier throughout the week, a network with a high amount of residential buildings vary less with this calendar factor. On the other hand, as residential buildings consume more DHW, a nonlinear dependency needs to be taken into account. The nonlinear characteristic of DHW can be investigated in Figure 19 during summer months. On this account, ANN has been found to be most suitable approach to predict demand.

Based on the ANN try-out, the most vital issue in the relative feature performance was the prior hour. After that the prior day and prior week. The social factor had a compelling impact on the forecast. This can be explained by the large share of buildings other than residential premises. These have presumably a scheduled routine which can be predicted more accurately.

4.7 Marginal Cost for Producer

Marginal costs are defined here as the additional cost of an extra unit output. In energy systems, the marginal cost function is discontinuous because investment and capacity are lumpy variables. The ongoing plant with the highest marginal costs are determining the overall price level of the system. The model's power plant costs are divided into two parts: fixed and variable costs. As the fixed costs of a power plant are constant, and are not altered by the amount of production, the marginal cost for the producer can be estimated by variable costs. The following table lists the cost factors which are counted in the simulation. Additional cost factors are described in Section 4.7.1 and Section 4.7.2.

Table 7: List of variable and fixed costs of a power plant. Adapted from (Ahlstedt, Koskelainen 1995, Koskelainen, Saarela et al. 2006, Drbal, Westra et al. 2012).

Variable costs	Fixed costs
Fuel costs	Repayment of investment
Variable O&M, standby	Fixed O&M
Run on and shutdown (incl. electricity and starting fuel)	
Taxes	
Emission allowances	

Since DHC is produced locally, the price varies between locations. The price level depends on various factors, including the utilized fuels, age of the plants and grid, the density of the network, the efficiency of the investments and management, the owner's yield requirement, as well as the size of the DHC system (Ahlstedt, Koskelainen 1995). Of these factors, the size of the system has a notable impact, as energy can be produced by cogeneration power plants only in large DHC systems.

The model consists of a pulverized coal CHP plant, a heavy fuel oil HOB, a biomass HOB fired with wood residuals, and a large heat pump. The thermal power output is 140 MW, 130 MW, 20 MW, and 10 MW, respectively. The maximum power output of these plants has been verified by comparing the amount of energy with an average fuel mix of a DH system. It has been simulated for an artificial DH system with a yearly heat demand of 750 GWh and a demand curve as presented in Figure 19.

4.7.1 Variable Costs

The variable costs for DHC are difficult to allocate because there are multiple factors to consider. Additionally, the allocation of costs for the production of electricity and heat can be executed in various ways depending on the characteristic of the DHC system. The energy method is utilized in this simulation. Nuorkivi (2010) describes that the energy method expresses the connection between fuel costs and the output of a power plant by means of the thermodynamic laws. The energy method defines the variable costs which occur due to heat production in a power plant. Also other ways to allocate DHC costs exist. In thermodynamic allocation, the exergy method is widely used, whereas in economic allocation, the benefit distribution method is mostly utilized. The selection of allocation methods depends on the actual energy market[9]. In Finland for instance, DH and electrical power operate on a saturated market and the costs for producing two outputs out of one input is allocated in a market based way (Järventausta 2015).

Based on the accounting methods by Difs et al. (2010) and Koskelainen et al. (2006, pp. 465-468), the simulation in this thesis will use fuel prices, European emission allowances (EUA), taxes, and Operations and Maintenance (O&M) costs as in Appendix 2 presented for calculating the marginal costs of DH plants. The values used are actual taxes and electricity spot market prices for the year 2015 and average fuel prices reported in official statistics from the same year as well. The fuel prices paid by individual companies can differ from the reported average prices, as prices vary depending on the negotiation power, contracts, and composition of the DHC system.

The electricity price is an additional variable in DH systems especially with cogeneration power plants and heat pumps. At present, CHP plants are driven depending on the DH load, and the revenue of electricity fluctuates highly. However, as revenue streams depend on the price for electricity, short and long-term price predictions are of interest. Electricity price forecasting is therefore a well-studied topic as obligations are highly traded in the market. The marginal cost of DH on the CHP power plant and on the heat pump are based on the electricity prices which are determined in the Nordic electricity market. Hence, the price for DH can be computed a day before, when the spot market prices are known. Electricity prices varied between 0.30-150.10 €/MWh, with an average price of 29.70 €/MWh (Nord Pool Spot 2016a).

An electricity spot market is a short-term power trading market that operates a day in advance of the actual physical delivery of power (Nord Pool Spot 2016b). The generation decisions for the next day result mostly of an auction where producing, selling and consuming agents submit price-quantity curves. Even though loads vary and are supplemented in the intraday market, most of the large power plants in DHC systems cannot participate in these markets. Therefore, heat generation costs with CHP plants can be relative truthfully predicted one day beforehand.

Taxes were calculated according to the Finnish legislation: heat delivered to the network is taxed, whereas electricity is not, as the latter is traded on the multinational electricity market (1996/1260 §7). If heat is generated in cogeneration plants, 90% of the fuel used for the heat part are subject to tax (1996/1260 §10). Heavy fuel oil is taxed with heat generation, whereas wood residuals are not taxed.

The total variable costs of power plants can be calculated as follows [€/MW]:

$$VC_{thermal\,power} = \frac{fuel}{efficiency} + O\&M_{var} + Tax + EUA \tag{15}$$

Appendix 2 shows the variable costs of the power plants and the heat pump. An interesting point is that while the revenue of the CHP plant increases with increasing electricity prices, heat pumps generate the highest value when the electricity price is low. Since the electricity price has been in the recent years very low, the utilization of large heat pumps in the DHC system has been seen as beneficial. The variable cost of heat pumps depends on the hourly changing electricity price, electricity transmission costs,

[9] These market dependencies are further discussed in Section 4.7.

electricity tax, coefficient of performance (COP), and variable O&M costs. Therefore, the variable costs are calculated as follows:

$$VC_{heat\ pump} = \frac{electricity+transmission+electricity\ tax}{COP} + O\&M_{var}, \tag{16}$$

COP of a heat pump is defined as the ratio of heating or cooling provided to work required. Higher COPs equate to lower operating costs. The cost factors for the large heat pump in the system are presented also in Appendix 2. The variable costs for all plants are shown in Table 8.

Table 8: Variable costs for simulated power plants.

	Output	**Variable cost**
Pulverized coal CHP	140 MW_{th} 90 MW_{e}	25.60 €/MWh+16 €/MWh_{th}
Heavy fuel oil HOB	130 MW_{th}	78.40 €/MWh_{th}
Wood residual HOB	20 MW_{th}	31.60 €/MWh_{th}
Large heat pump (average)	10 MW_{th}	28.50 €/MWh_{th}

The target of the DH pricing model is to minimize the total cost of delivering the required amount of heat for each hour of the year. For this, the calculation of HOB marginal costs is straightforward based on the factors listed in Table 7. As expounded earlier, the cost allocation of CHP is more complex. A simple approach is to target the alternative costs to one energy form, and residual costs are targeted to the other energy form as presented in Koskelainen et al. (2006). Hence, the model calculates the operating costs in relation to the market price for electricity and the leftover are targeted to heat. If the revenue for electricity exceeds the variable costs for heat generation, a negligible cost of 1 €/MWh_{th} was set. Variable costs and consequently profitability of heat pumps depend on the price of electricity as well.

The cost structure of the variable costs is further illustrated in Figure 20. The average revenue from selling electricity is here presented as a negative expenditure. These are dynamically illustrated for one year in Appendix 3.

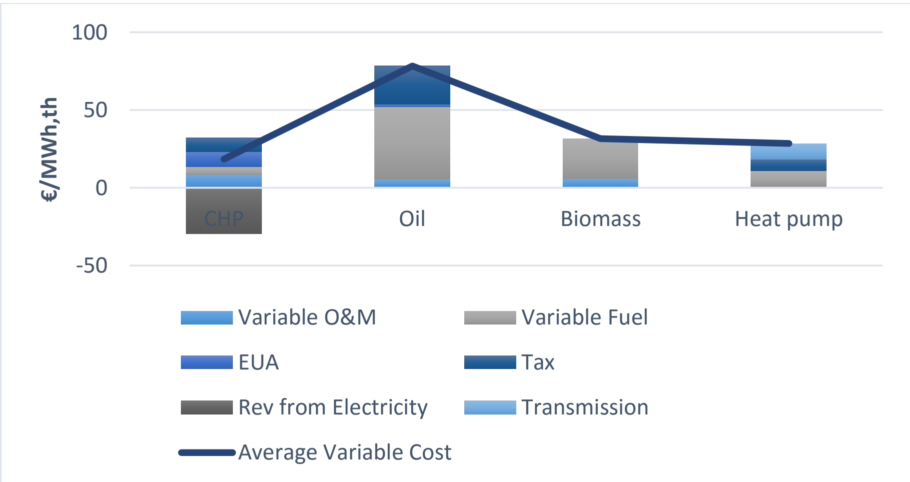

Figure 20: Variable cost structure of power plants simulated in the DH system.

The variable cost of DH is one fraction of the total energy price for DH[10]. In Finland, the average price of DH was approximately 75 €/MWh in 2015 (Finnish Energy 2016c). In practice, the energy costs paid by the consumer contain additionally the value-added tax (VAT)[11], capacity costs, network losses, security costs, and profit margin (Koskelainen et al. 2006). When considering an hourly based price for DHC, capacity and delivery security payments be reckoned. These additional costs are seen as the constant which cannot be affected by DSM. Therefore, the thesis continues with the simulated prices.

4.7.2 Fixed Costs

Even though the fixed costs have no direct influence on the merit order of the power plants, the fixed costs are considered when developing a model for satisfying long-term demand. The fixed costs of power plants during operation include fixed overheads, financial costs, depreciations, taxes, employee salary and insurance. Similar costs are due to the grid network. These costs are timely located to the beginning of operation and are characterized by considerable capital costs, such as the construction of a production plant, grid, pump stations, heat exchangers, machines and facilities (Koskelainen, Saarela et al. 2006).

Table 9 presents the estimated capital costs for the above mentioned power plants. The data is retrieved from electricity generating plants and thus gives is seen as suggestive. Since capital costs are one-time costs with long payback times, these need to be pro-rated over the lifetime of the power plant (Drbal, Westra et al. 2012). In this model, the calculations utilize a computational life time of 20 years with an imputed rate of interest of 6%. This returns an annuity factor of 8.7%.

Table 9: Fixed costs of power plants utilized in the simulation. Adapted from (IEA 2010).

	Capital costs €/kW$_{th}$	**Fixed O&M €/kW$_{th,a}$**
Pulverized coal CHP	1450	16
Heavy fuel oil HOB	200	10
Wood residual HOB	400	20
Large heat pump	900	10

4.7.3 Optimization Problem

The target of a producer is to determine either maximizing hourly benefit or to provide minimum stable output for each hour. The two targets ensure that enough generation is attained so that actions are profitable or at least enough generating output is acquired from the power plant to remain in continuous operation. As the shutdown and start-up process of the power plants are affecting the production costs, it is necessary to optimize these with a mixed integer linear programming (MILP) problem is presented. The MILP problem is non-convex and created as an integer domain by defining at which time the plants are switched on and off (Belegundu, Chandrupatla 2011). The formulation is compassed by expecting the CHP plant to be on service the whole heating period.

After that the model assumes that the problem is convex which can be solved with a linear programming (LP) problem with a dual simplex algorithm. This problem is chosen, since

[10] The average energy price from the statistics includes energy costs and power fee (Finnish Energy 2016c).

[11] Used VAT for Finland was 24% in 2015 (European Commission 2016).

it occurs in many practical economic situations where profits are to be maximized or costs minimized with constraint limits on resources. Furthermore, LP problems have been found to be a versatile solution finder with a fast calculation time. (Belegundu, Chandrupatla 2011) In principle, LP problems are solved by computing all basic solutions and selecting from the feasible ones the one with an optimal objective function value. The LP problem is calculated with Matlab's LINPROG dual simplex algorithm. Dual feasible solutions can be found while the standard approach to carry an LP model is not available (Belegundu, Chandrupatla 2011). The algorithm iterates, attempting to maintain dual feasibility while reducing primal infeasibility, until the perturbed problem is both primal feasible and dual feasible (Belegundu, Chandrupatla 2011). The objective function for the LP problem is formulated as follows:

$$\min(\textstyle\sum_{i=1}^{4} p_i(t) \times x_i(t)), \tag{17}$$

where

$p_i(t)$ is the price [€/MW] at given hour *t* for each production facility *i*,

$x_i(t)$ is the amount of power at given hour *t* for each production facility *i*.

The objective function is subject to:

$$x_i \leq x_i^{max}$$

$$\sum_{i=1}^{4} x_i(t) \geq d(t)$$

$$x_i \geq 0$$

$$i = 1,..,4; t = 1,..,8760; i \in \mathrm{R}^n$$

where

x_i is an optimization coefficient vector,

x_i^{max} is the maximum power load [MW] at each production facility *i*, and

$d(t)$ is the predicted demand [MW] in the DH system at given hour *t*.

The time-step *t* is expressed as a one-hour step of a year but the model can calculate also shorter periods. Shorter time intervals, such as 10 minutes, have not been found to be necessary because of the slow thermal characteristic of the system and because the price for electricity is delivered in one-hour intervals. The MPC algorithm predicts the effect of controlling decisions every 10 minutes over a time horizon of 1-24 hours. This has not seen to be a problem since weather forecasts are also given in less frequent intervals.

In addition, a penalty for operating the plant below its maximum capacity is introduced by increasing the marginal costs of the given plant by 5%. The described penalty was added in order to mitigate the operation of the plants below their maximum capacity. Additional start-up and shutdown costs are added by increasing DH price at a given hour by 10 €/MWh for the CHP plant, biomass plant, and oil plant, respectively. These one-time fees are added to the hour when the state of the plant changes. These were associated with the decrease in efficiency and shutdown costs of the plants. However, as the shutdown costs were one-time expenditures, the algorithm might continue decreasing load, if the marginal cost of the CHP was high. This is further discussed in Section 5.3.

4.7.4 Discussion of Methods

In order to verify the model, the input and output data have been analysed and the results have been compared to the Finnish Energy's statistical data. However, as stated in the beginning of Chapter 4, the simulation is an approximation of a real world DHC system. First, network costs, including heat losses and pumping power, are neglected. Heat losses in the network occur depending on the length and structure of the network and average size of the pipes. These can count 4-20% with a mean of 8% of the overall sold energy and therefore even determine the merit order of the power plants (Koskelainen, Saarela et al. 2006).

The simulated DH system takes additional costs for start-up and shutdown with a one-time price increase. In practice, the cost for ramp on or off depends on the length of the initial state. Besides the fixed on-ramped position of the CHP plants, the model assumes that the switch is possible on an hourly scale. However, these types of studies are made earlier as well (Syri, Mäkelä et al. 2015). Network flow problems, including maximal flow and cost of network flow, can be solved by dynamic programming (Belegundu, Chandrupatla 2011). With an increasing amount of start-ups and shutdowns, a dynamic optimization problem, which takes the position of the network flow into account, would increase accuracy. Unit commitment decisions discuss the length and thus the excess costs of start-up and shutdown states in power plants.

4.8 Optimizing Load Control System

The most positive effects of DSM are reached with a large and broad share of DHC consumers. Depending on the DHC system, the target of peak load reduction varies. In order to avoid the shifting of peak load from one hour to another, a market-based auction system is introduced. An auction system can be realized with multi-agent technology where smart control devices act online as agents (Persson, Davidsson et al. 2005). An agent is a stand-alone software system which is capable of flexible and autonomous action, and observes and acts upon its environment and directs its activity towards achieving a system wide goal (Wernstedt, Davidsson et al. 2007). The method described gives a favorable base for the DSM operator system. With a multi-agent system, a virtual auction platform for the thermal buffers in buildings can be formed.

For this thesis, a proposal for a load balancing system is presented as shown in Figure 21. The system exchanges data with the producer and each customer in a two-way communication system. The auction concept strives to achieve a preset DSM target by minimizing one by one the marginal costs of the consumer. The capacities of individual passive storage are managed in a VPP platform in which storage units are dynamically charged and discharged.

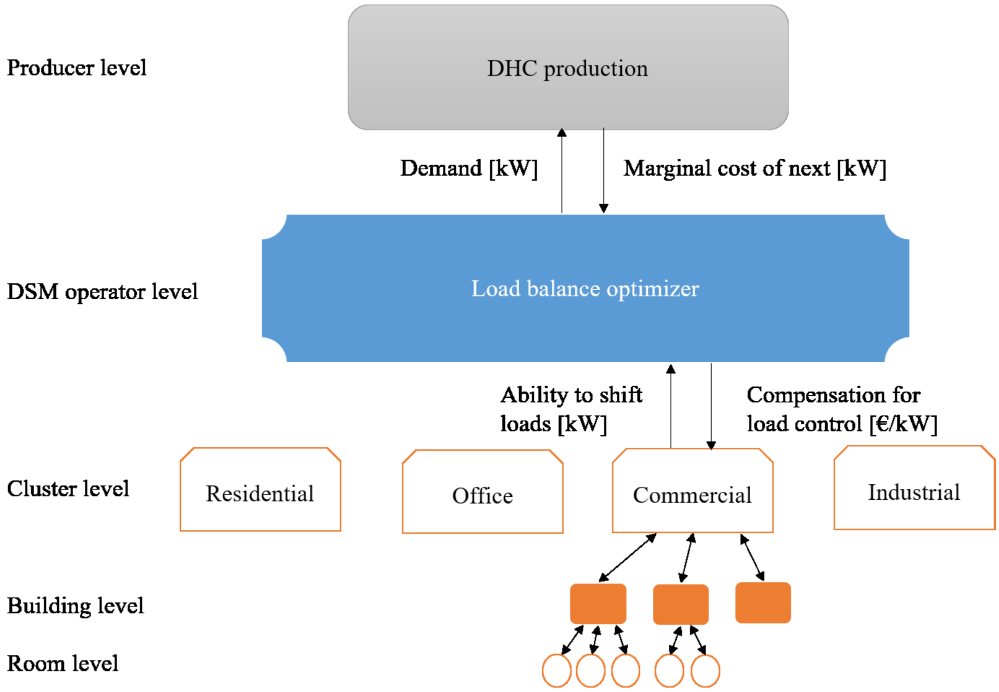

Figure 21: Schematic of the load ballancing system proposed in this thesis.

The process can be described in words in the following way:

1. The input data for decision-making reveals the need for DSM. An auction request, detailing information about the desired amount of load which needs to be shifted, is distributed among the participating buildings.
2. Within the buildings, the request is introduced to the control devices, i.e. agents, which predict the demand for the room and announces the amount of load which can be reduced and thereby the marginal cost for the consumer is formed.
3. The user can set the amount of enforced load shifting by an arbitrary value. By this the user has the opportunity to refuse to participate on the DSM event and consumer awareness is enhanced.
4. The DSM operator calculates which buildings should perform DSM at each hour with a piecewise LP problem.
5. The resulting information is then distributed among all participating buildings and the selected control device system implements the DSM action.

Step 4 is completed with n LP problem. It is assumed that the marginal costs have a convex characteristic and the cost for shifted peaks has a monotone increasing curve. The minimum of total costs can be therefore approximated by a piecewise linear function as presented in Figure 22.

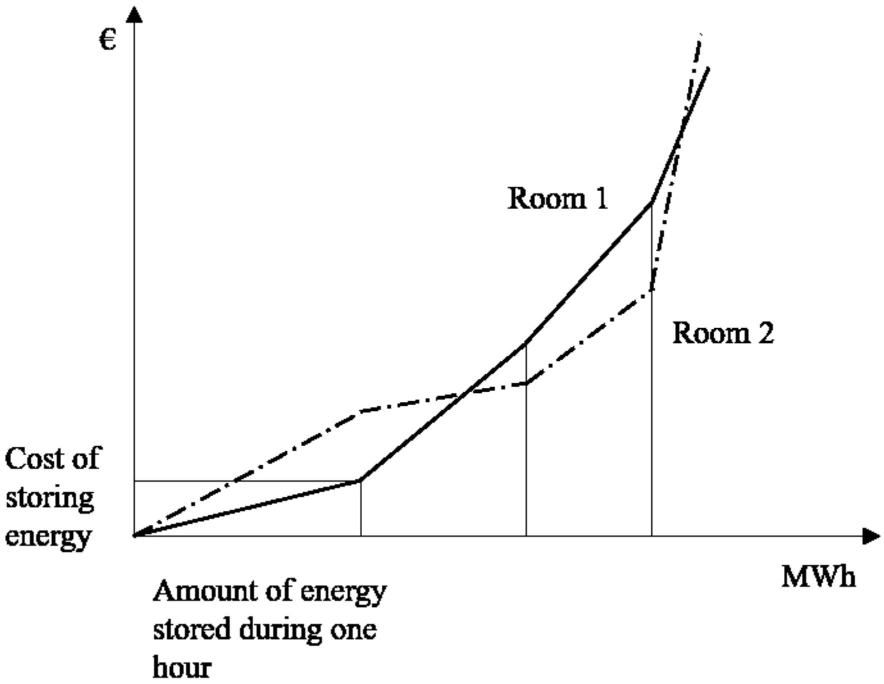

Figure 22: DSM allocation method for two rooms.

The figure presents the simple logic behind the allocation method. The MPC device sends a monotone convex function of the cost formation to the VPP platform. Storing energy during one hour costs each time more and the amount of stored energy decreases. The platform comprises the load balancing system shown in Figure 21 in which the amount of shifting load is targeted to each room or building unit. The linear functions of each room agents can be summed to a linear function for a building, and the building as a whole participates in DSM auctions.

This suggestive concept provides flexibility to the system. As the auction system optimizes the load at each hour, the risk of implementing the same optimization algorithm to the whole system is further avoided. With a large number of buildings, the connections and communication systems need to have a robust design. Therefore, multi-agent systems presented by Wernstedt et al. (2007) could interact in a reliable manner within the system. The researchers indicated that the system managed to hold auctions and divide load shedding even in case of communication disruption.

An auction system can also encourage to invest in other energy efficiency actions. Since some buildings are more applicable for load shifting than others, inferior buildings might find it beneficial to invest in thermal renovation. The consumers can also extend temperature boundaries and the arbitrage value for the marginal cost of participating in a DSM action. These incentives from the consumer can even more accelerate flexibility in the system and reduce total energy consumption.

As the thesis contains two simulations, i.e. one for the collected data and one for the building model, outcomes are described from both simulations in the following chapter. The simulations have utilized real outdoor temperatures and boundaries as described in Section 3.2.

5 Findings

In this chapter, major findings of the study are contributed. First, an analysis of the provided dataset is given with the focus on the largest potential for DSM. From this evaluation, the building stock is optimized starting from the building units anticipated to possess the largest DSM potential. This optimized load curve was then projected to the simulated DH system and cost savings, load variation, and the primary energy factor were investigated. Next, the simulation results of the room model are presented. The performance of the MPC algorithm is presented by figures of the radiator heat flow.

The following table sums up the most influential parameters affecting DSM. It describes the liabilities of the participants and indicates factors with actual cost saving potential. These factors have emerged during the thesis.

Table 10: Factors affecting DSM.

Factor	**Explanation**
DHC structure	Cost structure, merit order, size, policy
Production strategies	Demand forecasting, supply side management
Smart measurement devices	DSM potential identification and customer segmentation
Building structure and heat capacity	Amount of load control within constraints
Usage of building	Ease of occupancy prediction
DHW consumption compared to space heating losses	Relative amount of building energy offered to DSM activities
Inside temperature range	Extensive ranges enable more flexible operational environment
Former energy saving strategies	Setbacks may cause peak loads
Customers' willingness to participate in DSM	Freedom to participate with arbitrary value

The first three rows discuss DSM factors from the producer's perspective. First, the larger the DHC system is, the more flexible DSM activities can be. The production structure has a remarkable impact on the efficiency of DSM, as the dynamic prices are created based on the marginal cost of the power plants and electricity prices. The latter rows describe the influencing factors from the customer side. These are further discussed in the sequential sections.

5.1 Cluster Analysis

This section describes characteristics of the building clusters and analyzes their DSM potential. The results presented in this section indicate the effect of DSM on the energy usage of the buildings. In addition, it shows the effect in short-term production scheduling, and long-term value generation. The following graphics present the system price for variable DH production, electricity spot prices[12], and heat demand of the provided dataset with solid, dotted, and dashed lines, respectively. The data is retrieved from two sequential Mondays and show that system price peaks can vary in time and magnitude.

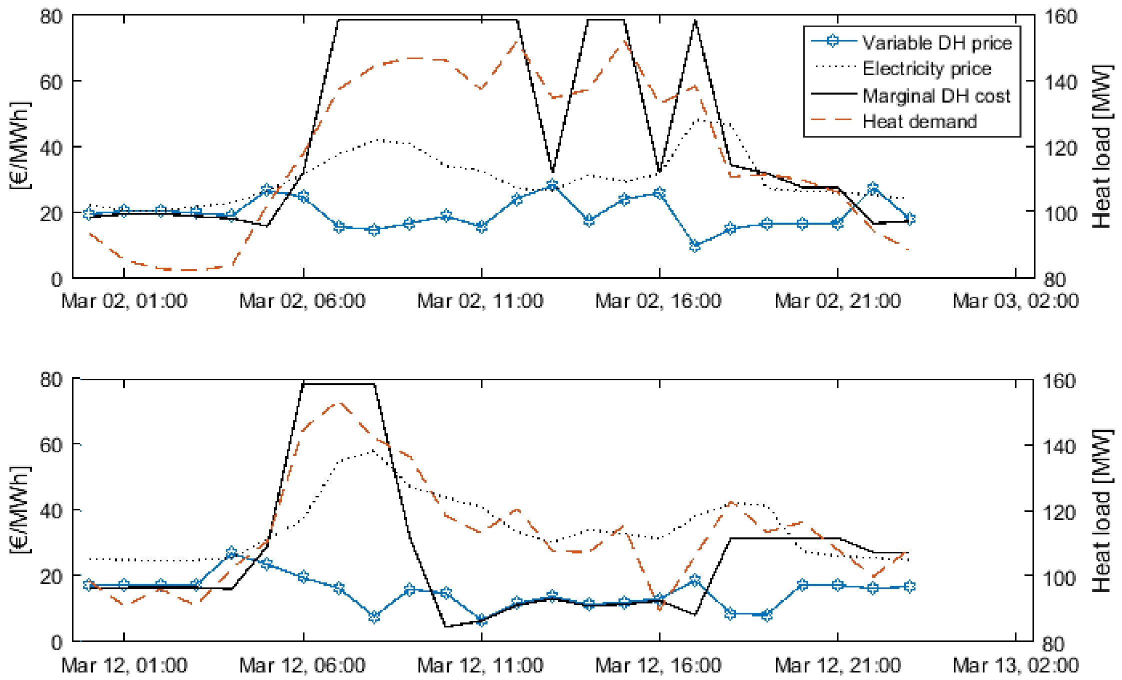

Figure 23: Variable DH cost based on the simulation, electricity spot price, and heat demand curve based on the dataset on two sequential Mondays.

Price peaks in electricity concentrate on mornings and evenings. Since DH consumption relies more on steady space heating, DH price peaks can differ from electrical price peaks. Moreover, as the graphics show, DH price peaks and demand peaks do not necessarily occur simultaneously. Consequently, predictive DSM should be applied with a dynamic schedule.

Next, load profile differences between clusters are analyzed. As discussed in Section 3.3, buildings are artificially divided into clusters based on their usage profile, temperature requirement, and occupancy pattern. These clusters are residential buildings, commercial premises, office buildings, and industrial buildings. Typically, load variation in electrical energy has a regular cumulative power consumption due to behaviour patterns. The variation differs typically higher during a day, and consumption profiles differ between work days and weekends. In heating networks, work day and weekend profiles depend largely on the investigated building, as seen in Figure 24.

[12] The electricity prices are stock market prices which in practice must be added taxes and transmission costs.

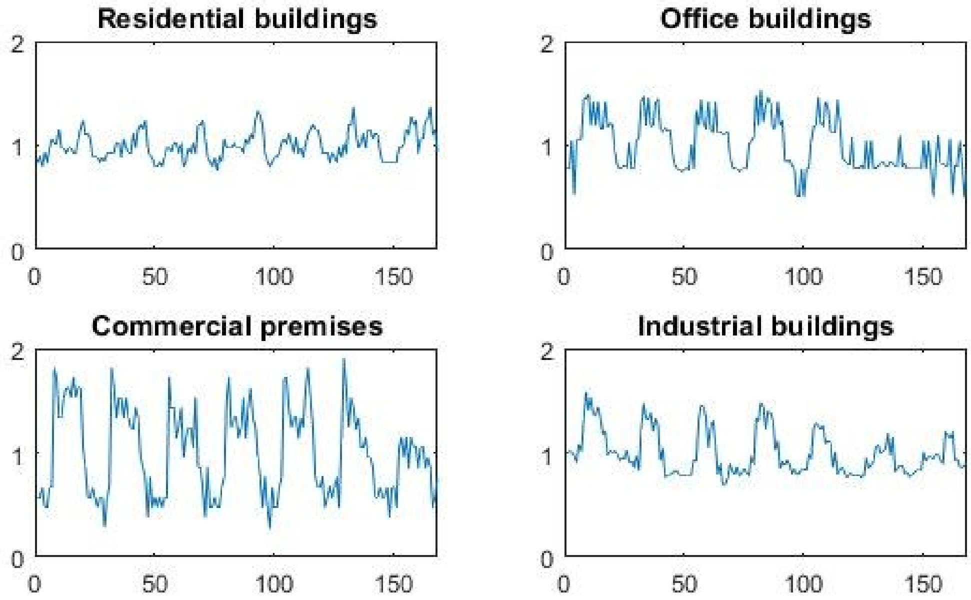

Figure 24: Relative load of one week in different clusters from the provided dataset.

As seen in Figure 24, residential buildings require heat throughout the week with a sharp peak in the evening. This can be explained with the consumption of DHW. As heat loads peak during the evening, residential buildings are less affecting the total peak loads during the morning and day. Office buildings in turn are completely off usage during weekends. The consumption profile of commercial premises shows a decrease on Sundays, whereas industrial buildings are consuming energy only for a short time during the day. Industrial and storage buildings have also lower requirements on insulation, but they might have a higher use of DHW and ventilation energy depending on the work specification. Based on recommendations, these buildings can have lower indoor temperatures which leads to a lower demand for thermal power, see Appendix 1.

When investigating only the load data, the buildings could have been divided into buildings with energy efficiency actions and buildings without. The artificially clustered data in the model show that buildings with existing night setbacks are affecting total system load most, as presented in Figure 25. Most of these buildings are office buildings and commercial premises. Therefore, buildings cannot be only investigated based on occupancy status, DHW usage, ventilation settings, and insulation design, but also on former energy efficiency settings.

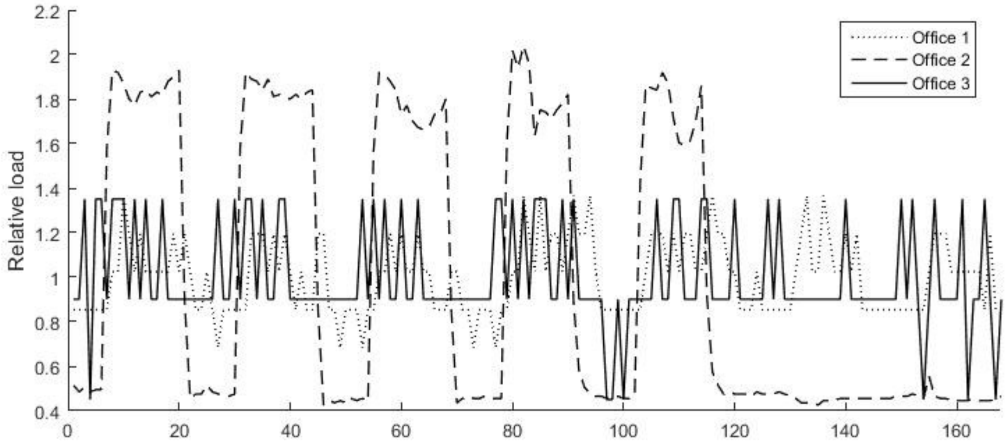

Figure 25: Relative load variation within office buildings in the dataset.

Because of these differences, further research on clustering techniques are recommended. However, the following section investigates predicitve DSM with the initial clusters.

5.2 Load Management in Buildings

An algorithm was developed which optimized with an LP problem the heat load for one day with constraints on occupancy and former energy usage. Sufficient inside temperatures were assured by forcing the heating system to increase several times in a day. The following graphic shows the initial and optimized load of an office building with high previous energy efficiency actions.

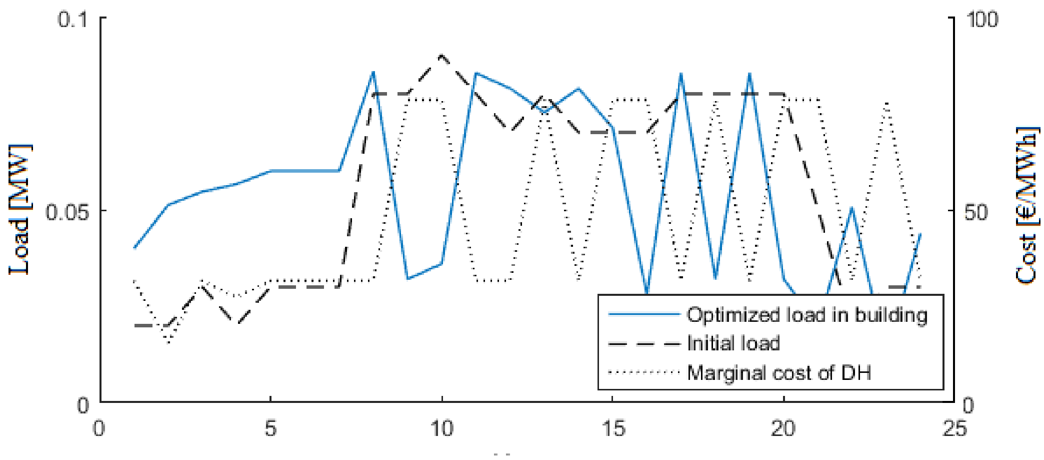

Figure 26: Initial load from dataset, optimized load, and simulated marginal DH production cost in a commercial premise.

The graphic shows that night time setback settings lead to a steep rise in the initial load profile in the morning. The optimization algorithm lowered load during high DH prices while maintaining a sufficient inside temperature. Therefore, load has been increased already during early morning hours and dropped when the system price increased. The overall load does not decrease to zero because DHW consumption and ventilation heating are calculated within the total heating demand.

Price signals for DSM can be based on peak demand, ToU tariffs, or dynamic pricing (Kärkkäinen, Sipilä et al. 2003). The first one is determined by system heat exchanger flow volume while the second is based on different energy prices during different time periods. The last one depends on hourly changing marginal production costs as presented in Table 8. ToU tariffs can be also dynamic, but in this thesis they are settled in advance. The simulation utilized ToU tariffs as stepwise changing prices and dynamic tariffs as hourly changing prices originated from the DH system model. The algorithm minimizes DH costs at each hour by either decreasing or increasing the load for periods of one hour without changing the total energy consumption of a day. An illustration of the results of hourly based price signals in a commercial premise is presented in Figure 26.

The same optimization algorithm as shown in Figure 26 is utilized to estimate cost savings in buildings caused by DSM. The upcoming figure shows short-term cost savings in office buildings from the dataset by shifting load from high prices to low prices. Figure 27 presents the load curve of an office building for 24 hours with steady outside temperatures. The graphics show the effect of predictive DSM depending on relative steady price signals, relative stepwise changing price signals, and relative hourly changing price signals.

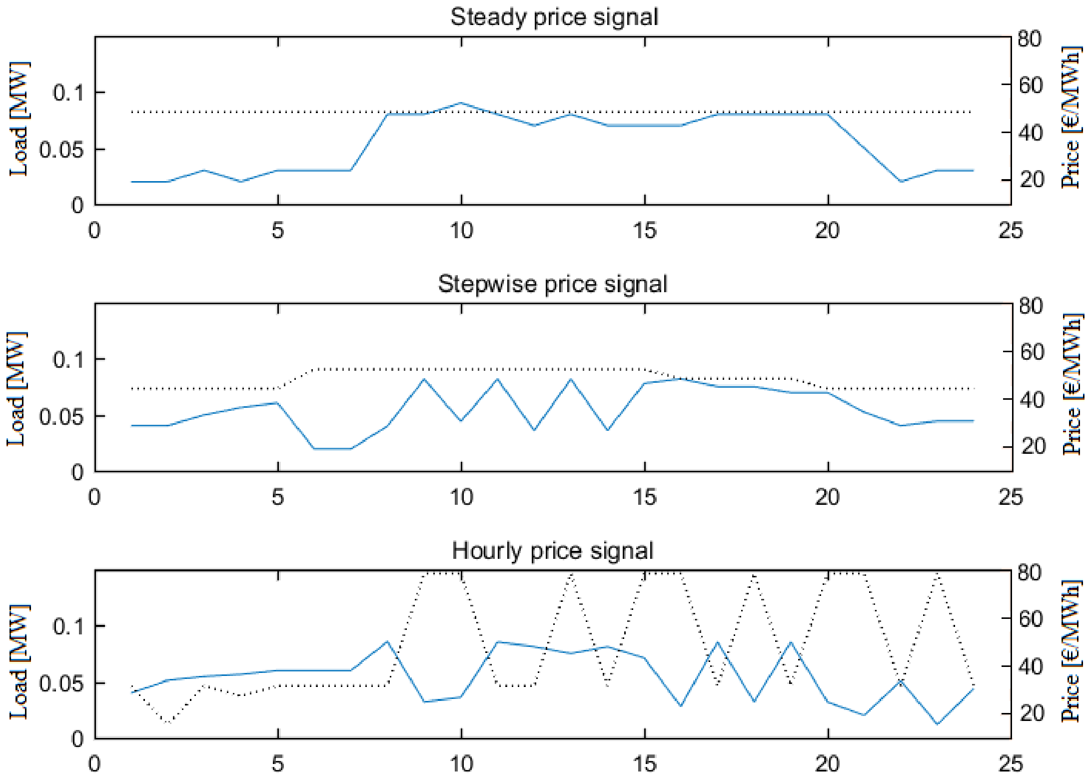

Figure 27: Optimized load profile as solid lines with relative steady price, relative stepwise price and dynamic price as dashed lines, respectively.

The upper graphic can be seen as the initial load since the DSM algorithm did not receive price signals. In the latter two graphics, the building started to charge itself earlier than in the initial load and correspondingly decreases during morning peak hours. As the buildings are still responding to earlier efficiency settings, the load decreases for the night.

Table 11 shows the financial results in relation to real heating data from an office building with an annual consumption of 511.6 MWh. The emerged cost savings are the result of shifting load from high DH prices to low prices without decreasing actual energy consumption as seen in column 2. The costs in numbers are calculated for a weekday in late February. When the optimization continues to later spring, the quantity of euros decreases due to decreasing energy consumption, but the percentage of costs remain at the same level.

Table 11: Heating costs in reference cases and with DSM during one day.

	Load	**Cost steady price**	**Cost stepwise price**	**Cost hourly price**
Reference	4.50 MWh	104.40 €	106.80 €	110.60 €
With DSM	4.50 MWh	104.40 €	102.80 €	99.40 €
Difference	0 MWh	0 €	4.00 €	11.20 €
Difference in %	0%	0%	3.90%	11.22%

The table shows two different results: first, the algorithm responds better to hourly changing input than stepwise changing input and thus can perform DSM more effectively. The algorithm forecasts the initial load for the day and optimizes consumption based on the price signals. The algorithm cannot perform DSM with steady prices for the lack of a stimulus. The second suggestive finding is, that the more the price changes during a day, the better cost efficiency is achieved. Consequently, the producer is able to charge depending on the actual load situation of the system. In addition, the saved costs shown in the table are assumed to be allocated directly to the customer. In practice, saved costs are allocated between producer and customer based on the heat supply contract.

The computed heavy mass office building has a heating area of 6200 m^2 and annual consumption 316 MWh. The payback time for an investment of 1000 € in a smart control system for the whole building can be estimated to be less than three years with hourly pricing tariffs and less than six years with stepwise pricing tariffs. These are estimated by counting a heating season of eight months for the Helsinki region and an interest rate of 6%. However, if the initial investment increases to 5000 €, the payback time increases to over 15 years and over 25 years which does not suit the building owner. Therefore, potential cost savings through DSM should be examined from the producer side. This is discussed in the following section.

5.3 System Response

The next section presents the initial and optimized demand curve from the system perspective. As seen in the previous section, DSM is best practiced with dynamic, hourly changing price signals. These price signals are utilized in the optimized demand curve. In the latter part of this section, costs of saving start-up and run down costs are estimated. The data used in the simulation originate from Helen's dataset which is aggregated corresponding more to Helsinki's actual building stock as shown in Figure 14 and enlarged to the size of the total DH capacity of 300 MW. The merit order of the power plants depends on the marginal costs, beginning from the facility with the cheapest marginal cost followed by the next cheapest until the demand is reached.

The optimization shown in Figure 26 has been extended to the other buildings so that 15% of the building stock participated in DSM. The first step was to optimize a sufficient amount of buildings which have been found to be applicable for DSM. The next step was to summarize the optimized data and calculate how the total load curve changed. After that, a new load curve was calculated. As stated in Section 2.1.3, ventilation heating and DHW are neglected which count 30-40% of the total heating load. Additionally, summer months from June to August were neglected. Therefore, 10% of the total load was controlled by the DSM optimization tool. Otherwise, it was assumed that the buildings can participate freely in DSM events.

The optimization rounds were allocated in the DSM operator cloud as described in Section 4.8. After each optimization round, the newly appraised demand curve was investigated and the producer agent formed a new marginal DH cost. The more even the load profile became, the less load was shifted by the subsequent building agents. When enough load was shifted, the producer agent dispatched a flat marginal cost which stopped the DSM operations.

The initial load curve presented in Figure 28 shows an interest period with two weeks in spring starting from a Monday and ending on next week's Sunday. The system consumed in total 57 GWh during these days. Since the target of this simulation was only to shift loads, total consumption neither decreased nor increased. The resulting total variable cost for DH differs from the marginal cost signals send to the buildings because they account the total costs including start-up and shutdown costs.

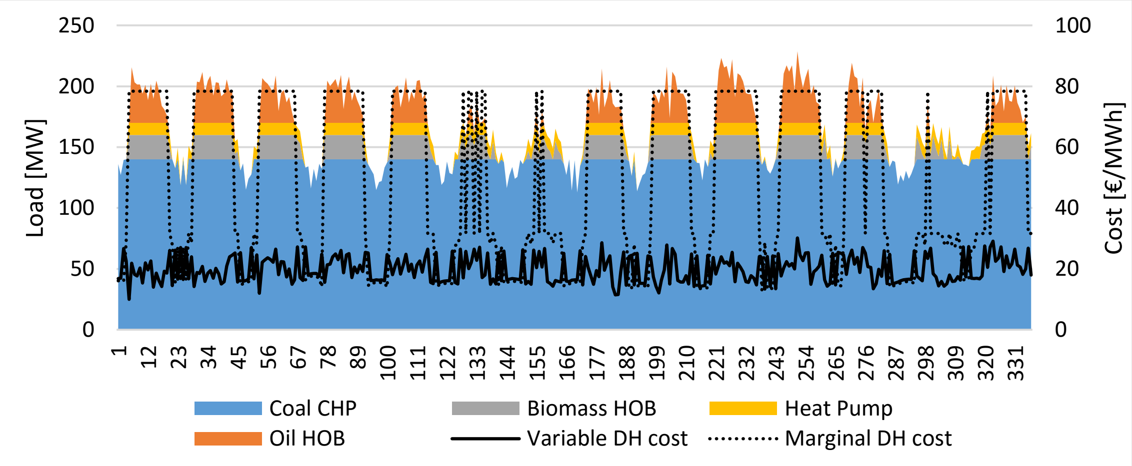

Figure 28: Original load curve, share of plants, variable DH cost, and marginal DH cost from the simulated DH system.

The algorithm was performed on 20% of the energy demand in the building stock including all clusters. The optimized load curve changes as seen in Figure 29.

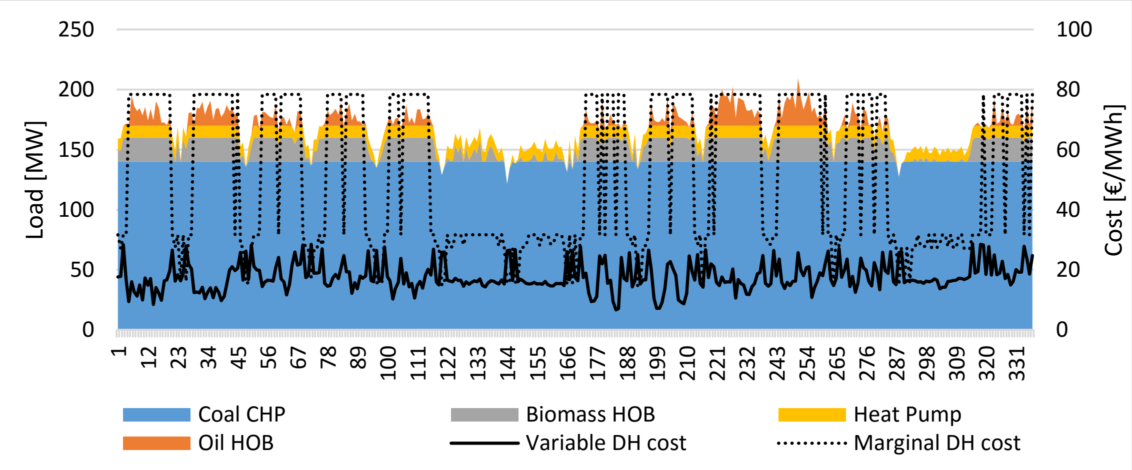

Figure 29: Optimized load curve, share of plants, variable DH cost, and marginal DH cost from the simulated DH system.

The figures show that peak loads could be decreased by up to 22% during on-peak hours and increased by up to 26% during off-peak hours. This lead to better power plat driving. As discussed in Section 4.7.1, the simulated marginal DH cost consisted only of the variable costs of production. This neglects network losses, financial liabilities, and profit margin. During peak load hours the marginal cost of DH generation peaks heavily because of the oil boiler. As seen in Figure 29, not all peaks could be mitigated. However, the effect of DSM is especially illustrated on a Saturday, i.e. hours from 121 to 144, as a remarkable price peak could be avoided. This is also reflected to the system price. As the building stock might not provide sufficient storage capacity, other elasticity actions can be utilized to mitigate the remaining peaks. The following table presents the financial results of the system during the period of interest. These are presented in order to give an understanding of the size of the numbers. After this, the computation results are provided for the entire year in Table 13.

Table 12: Comparing the original DH system with the optimized system during the period of interest.

	Consumed energy [GWh]	Average variable cost [€/MWh]	Total variable costs [M€]	Oil HOB start-up [-]
Original	57	18.7	1.061	14
Optimized	57	17.6	0.999	11
Difference	0	-1.1	0.061	-3
Difference in %	0%	-6%	-6%	-21%

Since the arithmetic average price for DH is around 75 €/MWh, and the average variable cost of DH is in the simulation 18.70 €/MWh, the percentage saving in energy costs can be estimated to approximately a fourth of the total DH invoice. By having an energy load of 57 GWh during the period of interest, the saved amount is 686000 €. The total energy demand for the whole year was 883 GWh. Original and optimized demand curves for the whole year are presented in Appendix 5 and the financial results are presented in Table 13.

Table 13: Comparing the original DH system with the optimized system during the entire year.

	Consumed energy [GWh]	Average variable cost [€/MWh]	Total variable costs [M€]	Oil HOB start-up [-]
Original	883	18.13	16.001	108
Optimized	883	17.7	15.688	62
Difference	0	-0.43	-0.313	-46
Difference in %	0%	-2%	-2%	-43%

The table shows that the average variable cost decreases less during the entire year than during spring and fall. Similar results are found in Difs et al. (2010) and they are described in Section 2.2.5. As mentioned earlier, it is difficult to make an absolute comparison between DH systems.

The system gains from decreased usage of oil boiler. The simulated oil HOB was started every day during the period of interest. As presented in Table 12, buildings equipped with predictive DSM devices are able to reduce load during peak prices and thus mitigate 21% of the on-ramping. During the remaining on-ramp phases, load could be decreased and consequent in an increase of revenue. As shown in Appendix 5, the mitigation for the entire year is even higher, cumulating to 43% of less on-ramping during the heating season. The following sections continue with the analysis of the DH system for the entire year.

5.3.1 Load Variation

Load variation within the system sank less than in the literature. This was also expected, since the main target of the algorithm is to reduce costs, not to smooth load profiles.

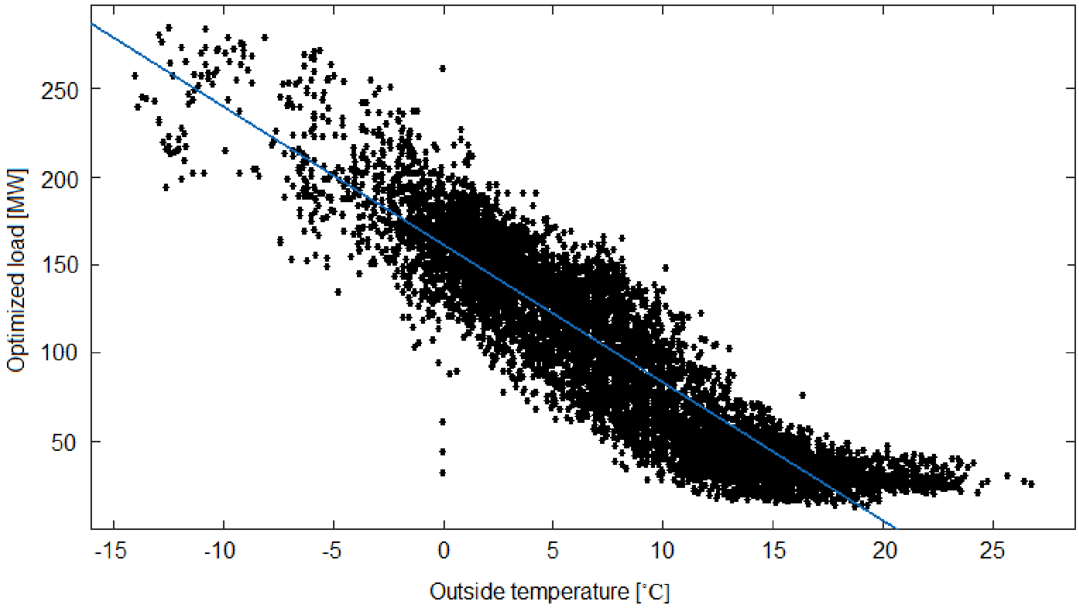

Figure 30: Polynomial fitting curve of simulated optimized load.

The results of the polynomial fitting demonstrate that the root mean squared error (RMSE) decreased from 25.16 to 22.21 and R^2 increased from 81% to 86%. The RMSE is a statistical method to measure model performance while R^2 describes how well the data fits to the regression line. Smaller RMSE values imply that prediction errors have decreased and increasing R^2 values indicate that the model explains the variability of the response data around its mean. As a result, demand forecasting has improved on the entire system. Furthermore, the results indicate that the CHP plant can be operated for modicum colder outside temperatures which has consequently an impact also on the on-ramp outside temperature of the oil HOB.

Figure 31 presents the distribution of both original and optimized load data. The histogram expresses the density of the underlying distribution of the data.

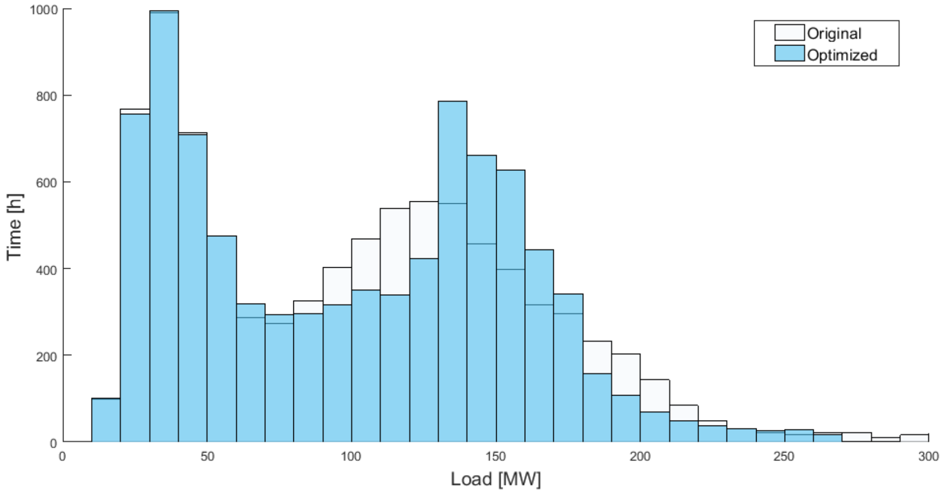

Figure 31: Histogram of original simulated load profile and the optimized load profile.

It can be perceived that the load has shifted to meet the maximal capacity of the CHP plant which is at 140 MW. Furthermore, the load shifted to decrease oil HOB utilization which starts when the cumulative load exceeds 170 MW. In the next section, further description of optimized system is given.

5.3.2 Screening Curves

After collecting cost data for power plants, screening curves of the costs per kW are submitted for the CHP plant, biomass boiler, and oil boiler. The producer can use screening curves to decide the generating unit mix. In this thesis, screening curves are presented to illustrate the cumulated demand curve and the share of the fuels of interest after DSM has been accomplished. Figure 32 presents in the upper graphic screening curves of the simulated DHC system. These are based on the fixed and variable production costs as listed in Table 8 and Table 9. The screening curve of the heat pump is neglected for its marginal power output. The lower graphic presents the load duration curve of the energy demand of the whole year.

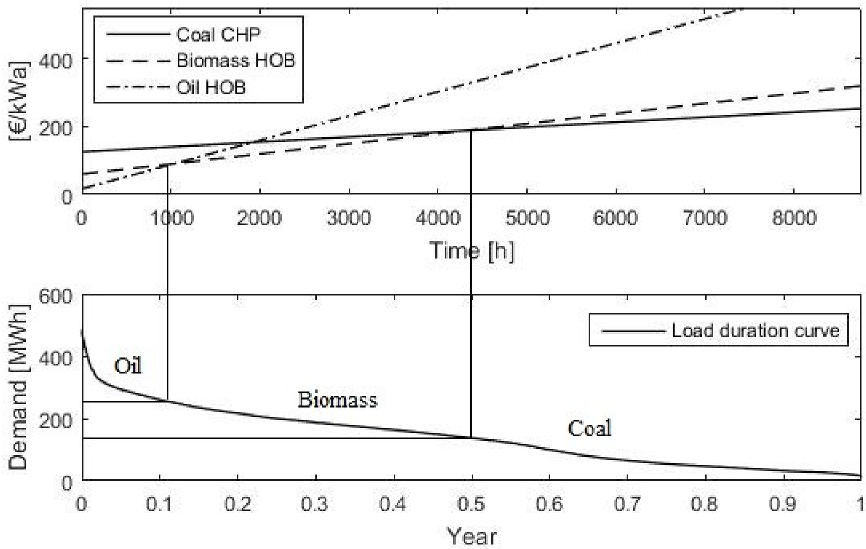

Figure 32: Screening curves (upper graphic) and load duration curve (lower) of simulated DH system.

The load duration curve gives the density function of consumed DH at the provided building stock. It is sorted in descending order and plotted against the time. By combining the screening curves and the load duration curves it is possible to estimate what fuel is fired during the year. The above shown load duration curve shows only the yearly plant utilization. However, fluctuating fuel prices, and electricity prices change the merit order in the short run. Also, demand fluctuations are affecting the need for on and off ramping.

5.3.3 Fuel Economy

This section provides computation results for fuel mix structure, primary energy factor and CO2 emissions. The calculations are based on the original data from the simulation as the reference case and the optimized data comprising 30% of the building stock as the optimized case for one year. The overall usage of fuels shifted from oil to the CHP plant. Table 14 presents the shift of utilized fuels in the simulated system.

Table 14: Fuel share in the reference system and optimized system during one year.

	Coal	Oil	Biomass	Electricity
Reference	89.0%	4.2%	4.2%	2.6%
Optimized	90.3%	3.0%	4.0%	2.8%
Difference in %	1.3%	-1.2%	-0.2%	0.2%

The primary energy factor describes the ecological impact in energy production systems. It shows the ratio between primary and end energy at the given energy carrier. In this thesis, the primary energy factor is calculated with SFS-EN 15316-4-5, which is expressly meant for calculating energy efficiency in DH systems. The method is based on multiplicative effect and it can be used to calculate the $CO_{2,DH}$ emissions (Pasanen, Bruce, & Sipari, 2013).

Through this the overall emission reduction can be calculated. The method is very sensitive to the factors used and the electricity generated in CHP plants is assumed to recompense condensing power. As the standard SFS-EN 15316-4-5 does not suggest primary energy factors for various fuels, the factors for oil and biomass originate from the standard EN 15603:2008 while the factor for coal comes from the estimation by Euroheat and Power (Euroheat&Power 2016). The primary energy factor for electricity is taken from the general EU-27 areas primary energy factor. CO_2 emissions are calculated with a similar approach as described in SFS-EN 15316. These are listed in the following table.

Table 15: Utility factors used in te calculations. EN 15603:2008 (Motiva 2016, Finnish statistics 2014)

	Primary energy factor	$kgCO_2/MWh$
Coal CHP	1.20	341
Biomass	1.10	0
Oil	1.35	284
Heat pump	2.5	209

The results are seen in the following table. As the simulated DH system included a CHP plant, the primary energy factor for DH decreased below one because the amount of generated electricity is subtracted according to the standard SFS-EN 15316-4-5.

Table 16: Change in primary energy factor for DH and CO_2 emissions in the simulated system for one year.

	Primary energy factor	**CO_2 emissions t_{CO2}**
Reference	0.66	329 400
Optimized	0.64	330 750
Difference in %	-1.9%	0.4%

The results indicate an increase in fuel economy, as the primary energy factor decreased by 2%. As the simulation neglected network losses, the result can be approximated to the total efficiency of DH production, which equals the relation between input fuel and sold energy. Perceiving this, the primary energy factors fits within the accepted fluctuation range (Finnish Energy 2015). In contrary, the CO_2 emissions increased slightly due to an increase in the coal plant utilization. Consequently, in order to decrease CO_2 emissions in a DHC system, the main fuel in the DHC system should be less polluting than fuel oil.

In times when demand was below the maximum capacity of the CHP plant, the system reacted heavily on electricity spot prices. As electricity prices peak during the morning and evening hours, and consequently higher revenues through the CHP plant are received, the signal advices to consume more in these hours. Similarly, during low electricity prices the algorithm forced the system to consume less. With the future highly volatile electricity prices, the DSM operator needs to drive the controllers carefully in order to retain system stability.

The optimization system looks forward to move as much load as the boundary values allow from hours with high marginal costs towards hours with low marginal costs. However, as the marginal cost for DH increased at spots of low electricity prices, the algorithm responded by decreasing consumption even more. Therefore, the price signal needed adjustment in order to urge consumption during low demand and thus even out off-peak hours. This has been achieved by implementing a MILP function: the CHP plant was during the hating time horizon constantly on, which lead to better correspondence of prices and cost signals were better directed at the controllers.

The producer side shows clear economic gains from predictive DSM. The results presented in this section are calculated with a model which optimized 15% of the artificial building stock's load. When extending the optimization to 30%, only marginal improvements are noticed because no energy conservation actions were added. At 60%, the system overreacted by decreasing load during low electricity prices and therefore risked the CHP plant operation. By 10%, the amount of available load to be controlled was too low. Now that the reaction of whole building units and the overall system has been evaluated, the next section focuses on the optimization of each room with a predictive controller.

5.4 Room Model

This section describes the simulation results of the MPC simulation. An ideal room model was simulated with the MPC controller. The simulation received as variables outdoor temperatures about the same time of interest as in the previous section simulated, with either steady, stepwise, or hourly price data. The controller simulated an office building as described in Section 4.4 with an occupancy status between 7am and 5pm. It predicted the state of the room 3 hours in advance and made control decision in 10 minute intervals.

The quadratic function in Equation 13 had as weighting factors 100 for occupancy and 0.001 for non-occupancy. Simultaneously, the weighting factor for the penalty of indoor air temperature change was set to 3. The following figures show the heating load change of the largest room shown in Figure 16. The figures present one week with even outdoor temperatures[13]. The simulation has been started one week in advance to ensure reliable indoor and building component temperatures. Therefore, the graphics start at point 1008 and end at 2016 which accounts one week in 10 minute intervalls. Figure 33 presents the heating load in the reference case. Here, the controller optimizes building load only on occupancy patterns, comfort and weather prediction, since the controller does not receive a price stimulus.

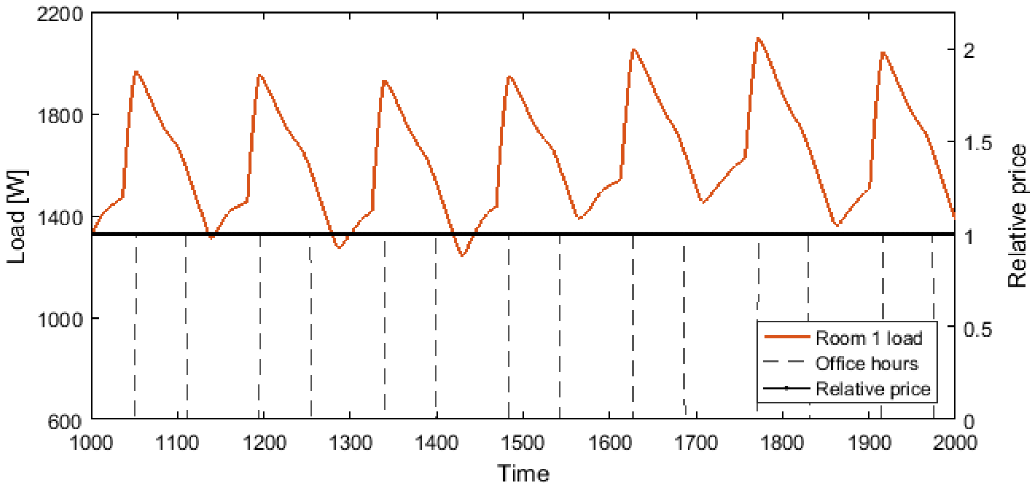

Figure 33: Optimized heating load in reference case during one week.

As seen in the figure, the controller drives automatically energy efficiency actions based on perceived external input factors and setback settings. The next figure shows the reaction of the controller with stepwise pricing.

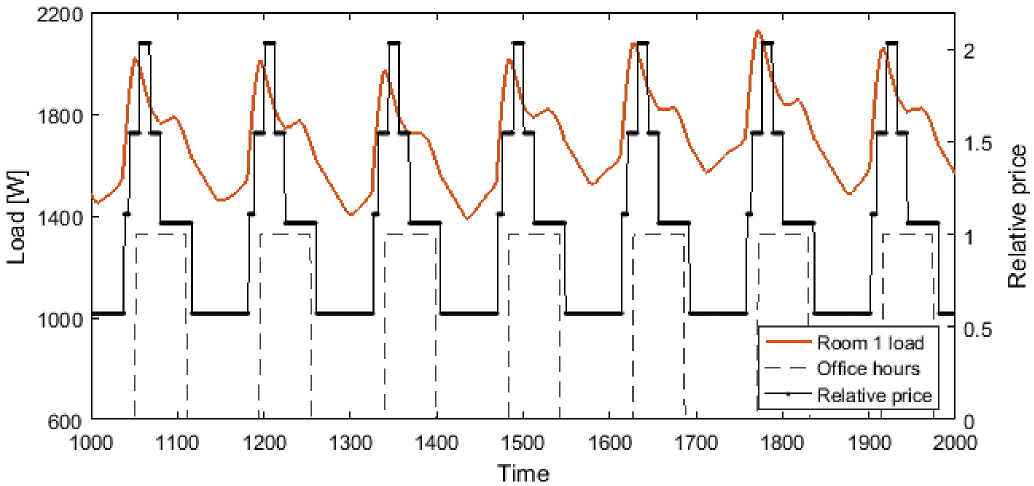

Figure 34: Optimized heating load with stepwise pricing during one week.

[13] Outside temperature variance was 1.53.

The stepwise pricing did not affect building load as wished, since preloading started only a little bit before occupancy but it did not load enough for the high price. However, the load curve shows how the controller increased load in the late afternoon, as the price decreased. This shows that the controller reacted on the price signal, but calculated that it is more efficient to heat during high price than in the night. In this case, the importance of the calibration of the controller is accentuated. The controller might have given too much weight on thermal dissipation minimization and consumer comfort. The stepwise pricing curve should be also discussed. The following figure shows the heat load profile with dynamic price signals.

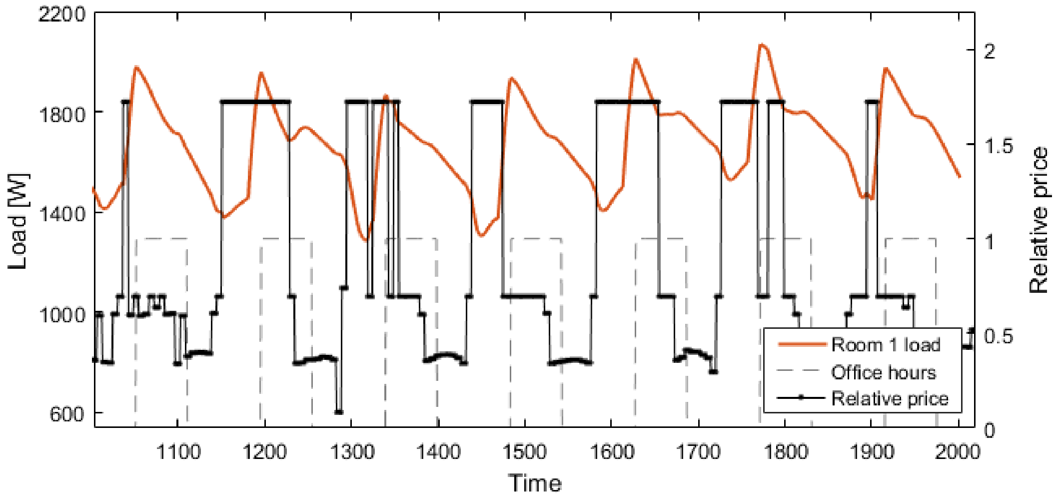

Figure 35: Optimized load with hourly changing marginal cost pricing during one week.

The relative price varies around the value giving the controller signals to either store heat beforehand or reduce load. The controller performed well and was able to reduce costs by keeping the reference indoor temperature at 21 ˚C on occupancy and 18 ˚C for non-occupancy. Minimum and maximum temperature ranges were set on 19 ˚C and 22 ˚C when occupied, and 16 ˚C and 22 ˚C when unoccupied. The inside temperature change during the simulation is shown in Appendix 4 for all cases. The following figure presents the percentage heat load difference between hourly changing price signals and steady price signals.

Figure 36: The percentage change in heat load based on dynamic pricing versus steady pricing in the simulated room.

The controller was able to reduce loads by even 25% and raise loads by 11% during the simulated period compared to the steady price optimization. These were further verified by feeding different outdoor temperatures and their corresponding marginal DH price. The rooms in the buildings acted differently based on to their specific thermal dissipation as described in Section 3.1. The rooms with less floor space were able to hold heat energy to some extent longer, as there was a larger share of building element per heated cubic meter air than in the large room show in the graphics.

The closer the assumed time of occupancy and time of preheating is, the steeper peak loads occur. Especially previous energy saving strategies, such as night setbacks, affect DSM targets since heating loads increase from one hour to another. Lower night time set points lead to a steeper increasing in heating load during mornings concluding in a decrease of cost savings. Concerns whether different settings jeopardize each other should be investigated in real examples. In case of simultaneous system peak load and building peak load, the heating strategy of the building is in need of adjustment.

The graphics illustrate how rooms are reacting differently to DSM. The cost function J of each room at each time step can be utilized to measure the participation ability as discussed in 4.8. The optimization problem was simulated in the room model by selecting a maximum DSM target, and inspecting which room wins the auction and is allowed to shift loads. In this thesis, the optimization was performed manually. Therefore, a future research objective could bring the concept into practice. In Wernstedt et al. (2010), building agents' ability to participate in DSM events weakened as inside air temperature approached boundary values.

The results of this chapter indicate versatile potential for DSM on the DH system model and in the room model. As seen in Section 5.3, the total cost efficiency of the system depends on the amount of buildings which are participating in DSM events and their hat load characteristic. This section in turn provided an agile concept on allocating DSM events within each room. This can be extended to a building stock as a VPP concept. Since customers are not directly gaining sufficient economic benefits of dynamic pricing, an approach for allocating revenue between customers and producers are introduced in the following chapter. In addition, an economic prospect for DSM is presented in combination with a business model proposal.

6 Market Environment

As the major technological findings were expounded in the previous chapter. It can be concluded that primary savings are determined to the producer, and therefore an analysis of the market environment is presented in this chapter. The base of this analysis is established by interviews with stakeholders and an expert panel, as described in Section 6.1. Next, the market potential for DSM in Finland based on the prepared simulation and statistics is analyzed. Out of these statements, a general market environment for DSM is characterized in Section 6.3 and as a result, a concept on valuing charged and discharged energy is proposed.

6.1 Concerns of Stakeholders

DHC companies have been interested in DSM in the recent years. Smart metering devices have brought knowledge and novel data analytic tools for better customer tracking. These tools have been utilized for instance for a more cost efficient pricing (Martikainen 2016). Companies have been initially interested in DSM in order to drive the same amount of plants also during short cold temperature periods (Turtiainen 25.7.2016). However, recent or former investment decisions, including modernization of plants, over capacity, heat pumps, and flue gas scrubbers, have led to a sufficient capacity also during colder days. Actual cost savings and interest in DSM vary highly between different locations and should be therefore considered individually. However, DSM value can be found by other means as discussed in Section 2.3.1.

The consortium Smart Energy Transition[14] gathered energy business experts to discuss the impact of digitization and electrical DR in a panel discussion (SET expert panel 6.6.2016). This discussion was a continuum on a two stage Delphi[15] questionnaire. According to the results of the questionnaire, demand elasticity will impact on the electrical system in 2030, as over half of the experts estimated that over 20% of peak demand is within DR (Ahonen 2016). This approximation can be utilized in large scale implementation as discussed in the following section.

The discussion included also many aspects on demand elasticity in DHC systems, since both systems are closely linked to each other. Both systems face obligations on digitization, automation, customer awareness, and information security. Benefits for energy companies in implementing DSM initiatives have become obscure, when understanding DSM only as an energy reduction application. By this, energy companies seem as unnatural supporters for energy efficiency actions. Therefore, regulation on energy control and building efficiency have emerged. As energy control devices have become more common, energy companies could find it beneficial to promote energy efficiency devices with DSM features. However, with the present pricing model, the customer cannot benefit from demand elasticity. The experts experienced that customers

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[14] Smart Energy Transition is a consortium led by Aalto University including also other institutes. The target is to analyze the institutional conditions for benefiting from the disruption energy technologies and investigate the policy implications. For more, see (SET expert panel 6.6.2016)

[15] A Delphi questionnaire is a structured communication method relying on a sample of experts. It aims to provide systematic and interactive forecasting information for policy-makers.

are utilized as tools to increase revenue for the producer. Therefore, the development of regulation and communication standardization should be emphasized especially on a natural monopoly market.

Another theme which emerged from the expert panel was to develop novel business models towards a service business scheme. Since most of the customers' interest on energy efficiency is finite, expert knowledge and service marketing are emphasized. Consumers can be motivated mostly with economic and ecological incentives, but experts found also other incentives in competition drive, technological interest, and gamification. DSM can be utilized as a tool to link hybrid systems, including DH heat exchanger and heat pump or direct electric heaters, within DH connected buildings. DSM can be also a tool to accelerate attitudinal change towards DH by providing flexible and transparent production and pricing data to the customer.

6.2 Large Scale Implementation

According to the Finnish statistics, the share of commercial premises, office buildings, and industrial buildings of the total space distribution are 16%, 15%, and 14%, respectively. Concluding from this study, these buildings are most suitable for DSM activities. As the focus of this thesis was on heavy mass buildings constructed between 1980-1990, the implementation is restricted to buildings constructed between 1960-2000, which account 25% of the buildings stock. Resulting from the expert panel, 20% of the energy consumption would be in the electrical sector under DSM control. By assuming these 20% would be also under DSM in the DHC sector, approximately 4 out of 5 of these buildings constructed in this period should participate in DSM.

The following table is collected from the Finnish Statistics. These statistics and estimations on specific heat load and energy index are utilized in the literature to assess potential building stocks to be connected to a DHC system (Finnish Statistics 2015). By taking the results of the room model from Section 5.4 into consideration, the average buildings constructed in this period of time are able to shift from 10% up to 25% of heat load during peak hours. Therefore, the maximum potential of shifting peak loads can vary between 700-1700 MW which is equivalent to 3-8% of the Finnish load demand[16].

[16] Total installed DH capacity in Finland was 23.27 GW in 2013 (Euroheat & Power 2015).

Table 17: Heated space distribution, DH energy demand, and DH heat load in Finland.(Statistics Finland 2009)

Buildings construncted between 1960 and 2000	**Connected to DH grid**	**Share of DH grid**	**DH heated area [Mm²]**	**DH energy demand[17] [GWh]**	**DH energy load[18] [GW]**
Commercial premises	54%	16%	28.8	3603.8	2.7
Office buildings	7%	15%	26.5	3310.3	2.6
Industrial buildings	40%	14%	24.8	3104.9	1.9
Sum			**80.2**	**10020.0**	**7.1**

The load shown in column 6 is calculated by taking a specific heat load for each building type into account. These heat loads are assumed for buildings constructed between 1980 and 1990. Because the large scale calculation accounts buildings also from other time periods into account, firm uncertainty should be noticed.

6.3 Market Structure

This section investigates the possible market for DSM in Finland. First, an analysis of the market environment is given. Next, the value creation of DSM is described based on electrical DR program recommendations. At last, a business prospect for DSM in DHC system is evaluated.

6.3.1 DSM Market Environment

The cost factors for predictive DSM consist of designing the DSM architecture, installing of hardware into the DHC system controller and buildings, and keeping up costs of the optimization system. However, a wireless Internet connection enable inexpensive communication with novel IoT applications. By this, the traditional network structure can be modernized and operations improved. Furthermore, IoT devices are enhancing efficiency and cost savings. Finally, IoT applications can encourage the energy business sector to develop disruptive services for adding additional value to customers. These services can change the expectations customers have on a traditional product, such as heating energy. In DHC markets, these could be created by adding third party aggregators. The smart grid enables utilities to offer new services at both the wholesale and consumer level by providing deeper insights on capacity demand, issue identification, and pricing options. These are all aspects of the DSM business environment which is summed up in Figure 37.

[17] A heating index of 125kWh/m² is assumed. (Finnish Energy 2016a)

[18] A specific heating load of 34, 36, and 38 W/m³ for each building type is assumed (Koskelainen, Saarela et al. 2006). The average room height is 2.7 m (D5 Suomen rakentamismääräyskokoelma 2012).

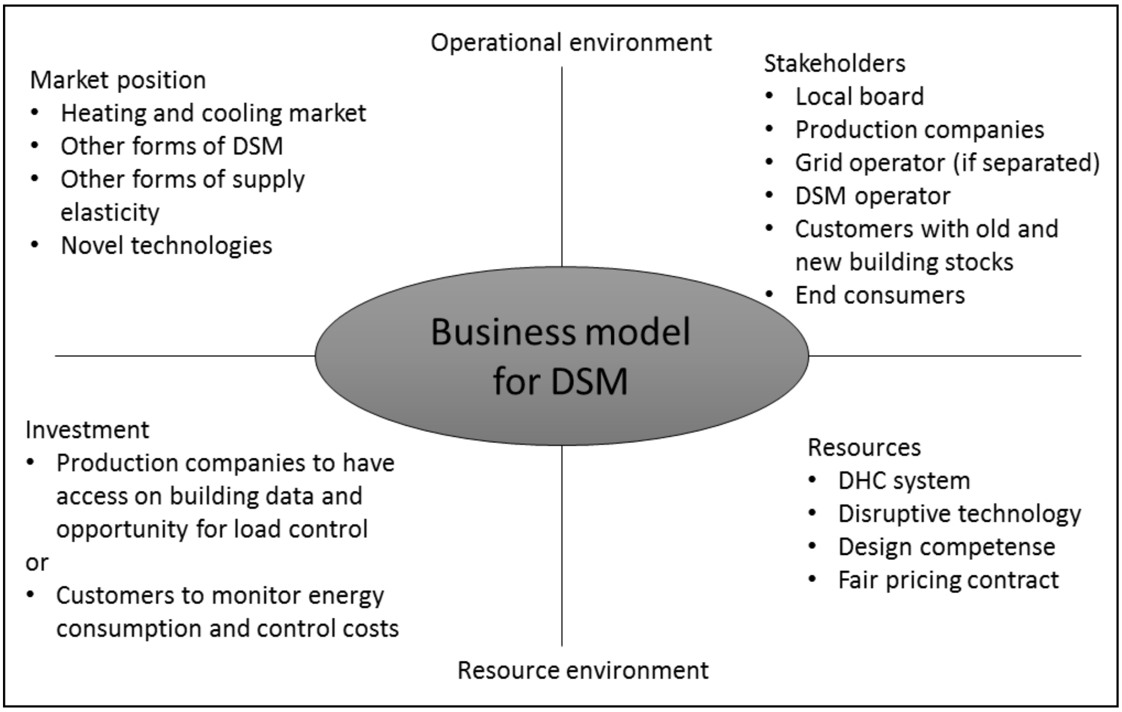

Figure 37: DSM business operation environment.

As expounded earlier, the DHC market is price inelastic. If the market mechanism develops towards a transparent pricing system which shows economic benefits to the producer and the customer, DHC has the possibility to become more price elastic. Price elastic markets enable an operation field for new businesses, as the price equilibrium strives towards an optimal balance.

When designing a business prospect for DSM and dynamic pricing, it has to be perceived that customers do not necessarily want to receive varying energy bills, as the monthly budget is precisely divided. This is registered in the electricity sector, as a small amount of consumers has taken the opportunity to adjust consumption. One reason for that could be the lack of interest and insufficient automation. Also, consumers are restricted to habits. For this reason, it seems beneficial to start implementing DSM devices to customers that have a sufficient amount of liquidity, and expertise on optimizing their energy invoice.

Out of the clusters described in Section 3.3, office buildings and commercial premises have the largest potential for DSM, as these buildings require a large heating amount, and their occupancy and marginal cost of the consumer can be easily determined. Furthermore, these building possessors are more likely to be interested in professionally decreasing energy costs. The second largest segment is joint-stock property companies which are renting apartments. These have a centralized policy making process. The following segment comprises of the privately owned housing companies which can make also higher investment decisions if desired. On the other hand, small building stocks might be more willing to reduce heating energy, as the consumer is closer to the decision-maker. Especially single-family houses are interested in energy conservation (Hellmer 2013). However, these buildings are due to their negligible heat capacity out of the scope of the thesis.

If the investment decision comes from the customer's side, a disruptive wave on predictive DSM devices is hard to achieve. This is due to slow retention of the building stock as well as the dominant market position of DHC. Still, energy efficiency in buildings is improving for example as the radiator system is renewed. Smart metering devices, and smart grids are found to bring cost benefits to all participants and the Energy Efficiency Directive (2012/27/EU) set by the European Union brings additional targets on energy efficiency[19]. As presents smart systems are able to only by energy deduction, DHC companies are losing revenue. Therefore, by installing smart meters with DSM feature on a fitting sized building stock, the producer can benefit from smart meters even though they decrease energy consumption. Additionally, producers are incrementing their sustainable appearance.

Another aspect on the DSM market environment originates from the producer side. When allocating DSM events to buildings, a promise of achieving load reduction via DSM during expensive DHC prices should be given to the producer, as power plant driving is scheduled well beforehand. As Valor Partners (2015) remark, producers possess the wish to reward customers for DSM events afterwards when the true value for the event is sorted out. However, these aspects can be untangled more dynamically by introducing the auctioning concept as described in Section 4.8.With the auction cloud system, the marginal costs on the producer side and marginal costs on the consumer side can be tracked. Based on the negotiated contract, the cost savings of the DSM event can be allocated. The relation of value creation and dynamic monitoring is further discussed in the forthcoming section.

6.3.2 Valuing DSM

Value for DSM can be found from both the customer perspective and the producer perspective. First, when assuming DH prices vary within the day to meet the actual utility costs, DSM participants can earn by adjusting load in response to current supply costs or other incentives. Also other customers find savings in their energy bill by a general decrease in wholesale prices resulting from DSM. Further value factors are illustrated in Figure 38.

[19] Member states of the European Union agreed to reduce 20% of primary energy consumption by 2020. The Energy Efficiency Directive (2012/27/EU) defines energy efficiency as the ratio between output of performance, service, goods or energy, and the input of energy. This universal definition covers most major aspects of the energy efficiency, such as production, distribution, consumption and the value created in comparison to the resources consumed during the whole process.

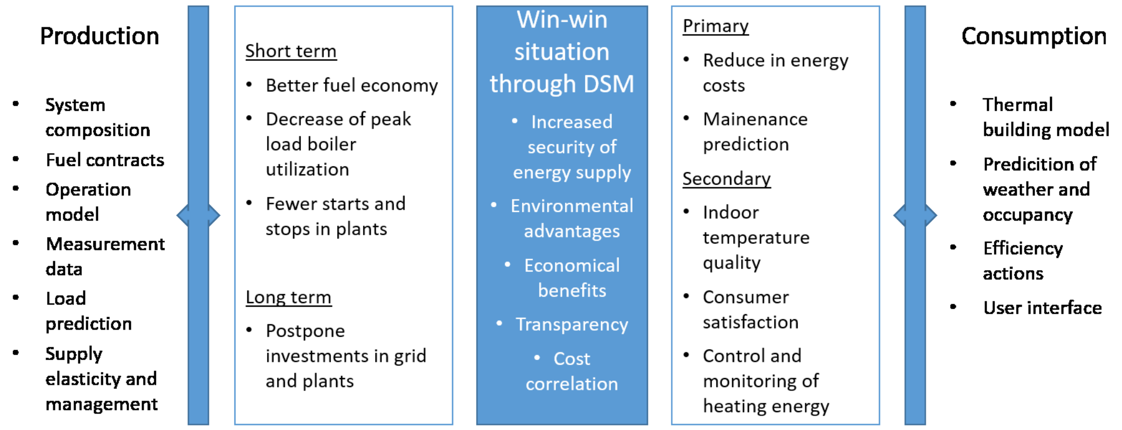

Figure 38: Win-win situation for producers and customers suggested in this thesis.

The outer columns present what the individual consumers can do to increase efficiency in their own systems. The central column shows how participants gain value through DSM as discussed in this thesis. The producer can list short-term and long-term values while the consumer side finds primary and secondary values. The blue coloured box lists which factors in DSM raise value for both participants.

As DSM prices are not determined in a free market as in electrical DR, valuing DSM actions becomes a major objective. The compensation for DSM is based on short-term increase and decrease in energy consumption. The amount of DSM is the difference between the normal consumption level that never occurred and the actualized consumption. This requires exact and smart measurement devices. These devices are required to predict the initial consumption patterns and calculate the difference of predicted and actual consumption. Energy companies can verify these by either utilizing their own forecasts or by using a rolling average as a baseline.

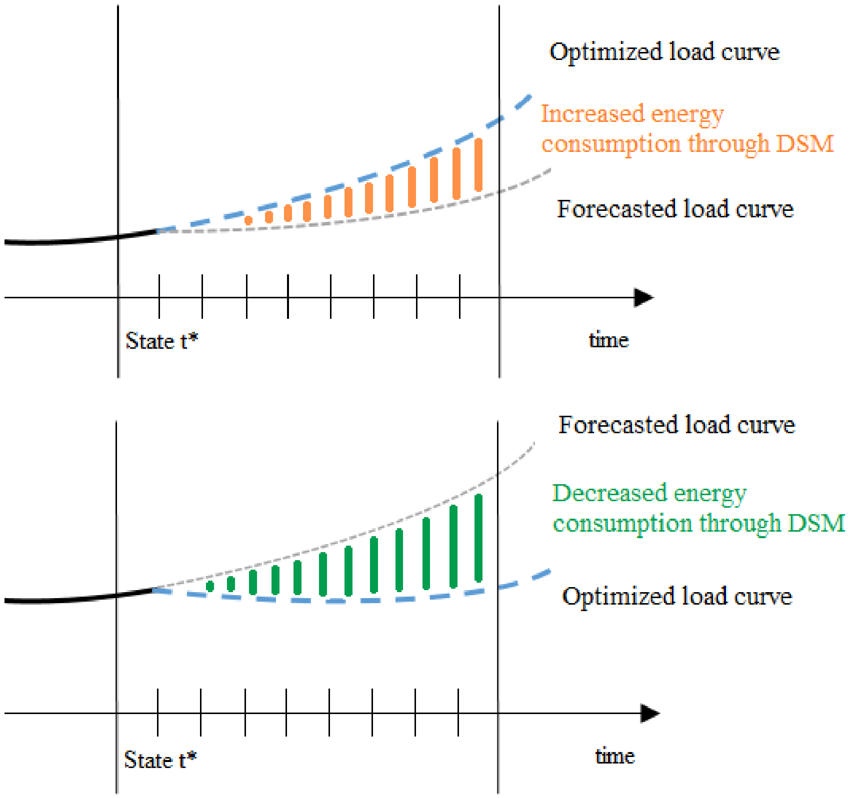

Figure 39: Approach on computing the amount of value for DSM.

Collection and efficient use of data is beneficial for both the energy producer and the customers. With accurate measurement devices, both producers and customers can yield an advantage. The devices with active data analysis routines will allow the producer to have valuable information about the customer demands and device configurations. Customer data can facilitate an enhanced management of manage the DHC system which may result in sustaining or even enhancing DHC market share in heating. On the other hand, customers will be better informed about consumption patterns and about the energy cost saving possibilities.

Energy efficiency actions, such as night time setback, can be implemented if the system will not overload. By two-side communication, the customer can take action on energy efficiency, receive an equitable compensation for “heating at the wrong time”, and the producer can operate the system in the most suitable way and take part in energy efficiency actions without jeopardizing its own system. On the other hand, customers need to be encouraged to utilize devices with DSM feature. This can be achieved by sufficient price compensation, a guarantee of sufficient indoor air temperature, and environmental factors. Out of these factors, DHC producers can influence the cost compensation with reasonable contracts.

DSM also provides other benefits that are not easily quantifiable or traceable, but can be vital to the DHC system. These include for instance improved customer choice, as customers have an increasing ability to manage their DHC consumption and cost formation. Another value factor could be the security of the system, as DHC operators are provided with more flexible resources to meet contingencies.

Since market technologies for DSM are emerging in a growing extend, the demand for regulatory reforms which allow utilities to capture the value of DSM increases. For instance, the Energy Efficiency Directive (2012/27/EU) of the European Union requires transmission system operators to allow consumers to participate in electric DR activities. When regulations are formed, the following factors should be taken into account: the ease of DR participation; increasing pricing transparency and the role of aggregators; providing reasonable pricing and compensation for participation; establishing communication channels; and legalizing all electricity markets where supply side participates (Smart Energy Demand Coalition 2014). As DR has been successfully piloted in the Finnish market, learned lessons can be implemented to DHC.

DSM can be performed with three approaches as suggested in Kärkkäinen et al (2003): direct load control by consumer, direct load control by producer, and third party aggregator. The customers can control the load of the building with DSM devices, or the producer can control buildings directly based on marginal costs. The first suggestion enables the separate control of the building heating system, but the reliable achievement of targets cannot be ensured. If the producer in turn controls the heating system of the customer, the threat of manipulation might put the customer's foot down. The third approach would combine the two stakeholders with a DSM operator, i.e. a third party aggregator. This aggregator would act as an energy service company (ESCO). These companies provide energy reduction services for customers. The latter approach is further discussed in the upcoming section.

6.3.3 Business Prospect

The implementation of a third party operator gathers the building stock as a solid thermal buffer through a VPP concept, in which the DSM operator signs contracts with both the customer and the producer. The VPP concept is utilized as a platform for the agent-based auction process. In order to gather a solid amount of reliable buildings with DSM potential, the DSM operator signs several contracts with buildings and manages DSM activities through the building agents for the agreed period of time. Simultaneously, the operator could provide load reductions as a service to the DHC producer.

In the literature, VPP auctions are described as sales of energy capacity as virtual divestitures (Ausubel, Cramton 2010). In the VPP auction, each buffer is an option contract for energy whose strike price approximates the marginal cost of the respective energy. Instead of selling a physical thermal buffer, the customer retains control of the building but offers contracts that are intended to replicate the thermal capacity of the building. These contracts are sold as divisible goods of varying durations and amount.

DSM devices can be either installed originally by the producer or by the customer. Traditionally, smart energy efficiency devices are bought by the customer since they directly save costs. On the other hand, pilots on electrical load profile control have been installed by the energy company. By developing pricing models and creating new contracts, both stakeholders can find cost savings. Manninen (2014, pp.79) reports that investment decisions could be accelerated when producers give customers an incentive to reduce peak loads, and customers can choose individually how to achieve these peak load reductions.

If heating energy is started to be seen as a service rather than a product, the target will not be to sell kilowatt-hours to the customer, but an optimal indoor temperature at the lowest possible cost. This gives the basis for an ESCO company. In contrary to free electricity markets, energy companies as natural monopolies are on a demanding position restricted mainly by regulation. Despite the fact that customers have the freedom to change the heating appliance, DHC companies possess strong negotiation power. Therefore, in order to ensure sufficient compensation for the consumer, negotiation ability and willingness to cooperate DSM events on both sides should be emphasized. By having a large amount of buildings with DSM devices, the negotiation power increases. This is also beneficial for the producer, since the greater the amount of buildings equipped with DSM controllers are, the better opportunities for flexible production are created.

Using individual smart metering and advanced DHC pricing, buildings, which participated in the DSM event, can receive compensation by the DHC provider. As presented in Figure 9, the producer would maximize revenue by operating the plants on full load but not shifting to the next threshold. As optimal power plant running is achieved only when a sufficient number of buildings participate in DSM, a functioning business prospect needs to be developed in order to raise the interest of all stakeholders. Reviewing this section, the business case is affected by following factors: customer interest, delivery security, production optimization security, and negotiation power.

7 Summary and Conclusions

This thesis observed the procedure and the resulting impact of DHC load control on the demand side. In this chapter, a review of the main objectives is given, including a discussion of used methods and a conclusion of results. Based on the limitations of the thesis, further research objectives are suggested.

7.1 Discussion

The basis of this thesis is the assumption that DHC producers are taking the initiative for developing a DSM strategy. Producers are as natural monopolies on the driver's place. However, as digital technologies and services are disrupting other traditional product and service sectors, the energy sector should also establish the inexpensive utilization of data. While smart metering and DSM have been found to increase efficiency and reduce costs for all participants, stakeholders are taking very cautious steps. The decision of making an investment on smart control devices with predictive DSM characteristics could be either suggested from the producer side or from the consumer side. As energy efficiency in buildings is becoming in a growing extent more common, DHC producers should consider on how rewards are allocated in the new situation of low energy consumption. As the statistics from the Finnish Energy Authority shows, DH prices are continuously increasing (Finnish Energy 2016a). At present, customers having the possibility to face increasing costs by energy conservation or by switching to alternative production.

These uncertainties on the energy and building sector could encourage policy makers to create regulation on this field. As DHC is already a highly regulated market and the political climate encourages at present more on deregulation, further actions might need time. When developing an active DSM strategy with predictive controllers, the monitoring of the price signals provided by the DHC producers should be developed in the same pace. Otherwise, intrigue from the producer side and suspicion from the consumer side may harm the good intentions of DSM.

As several times mentioned, the results of this thesis cannot be set as universal because every DHC system is different. Most of the CHP plants in Finland use biomass or peat as their main fuel and this trend is also continuing (Finnish Energy 2016a). Based on these facts, CO_2 emissions could actually decrease by implementing DSM. However, as the largest plants in Finland are utilizing fossil fuels, coal was applied in the simulation. At present, the price for electricity and oil is low. The financial results are smaller than the valuation of Valor Partners (2015) but are similar to the estimations of energy companies. It should be also noted that it is very difficult to predict future electricity and oil prices and their fluctuation profiles. Since plants and the grid are designed to serve for several decades, future profitability estimation can differ.

The thesis discussed DSM in existing buildings by utilizing the thermal inertia as passive TES. Nevertheless, the results indicate that predictive DSM should not only be performed with passive TES but to exploit also other techniques in a cost efficient manner. This would bring more flexibility to the DHC system, as different DSM strategies fulfill different needs within the grid. Additionally, boundary conditions were set rather strict with a high emphasis on consumer comfort which was especially overvalued in industrial buildings. Moreover, DSM was performed without energy conservation. In real case examples, changes in energy consumption would most probably occur. When developing energy efficiency strategies for buildings, it should always remark to sustain the quality of indoor air and prevent mold formation. Based on this discussion, the demand elasticity potential could be larger than in this thesis presented.

7.2 Conclusions

In this thesis, a model for predictive DSM system is developed. With smart building devices including a DSM feature, short-term peak demand loads could be mitigated cost-efficiently. This is achieved by utilizing the existing thermal inertia of the building stock as passive energy storage units. The possibilities which emerge from smart controllers and smart cities are discussed including current technological, economic, and sociological constraints. It is concluded that hourly changing DHC prices based on marginal costs of production could be beneficial in order to increase elasticity and thus improve flexibility in a DHC system. Without price variation, dynamic and predictive DSM cannot be implemented.

The thesis confirms previous studies on static load shifting (Kärkkäinen, Sipilä et al. 2003, Schmidt, Basciotti et al. 2013, Kensby, Trüschel et al. 2015) and also agile load shifting (Wernstedt et al. 2008, Johansson 2012) that DSM is reasonable for both DHC system operators and DHC customers. The potential rests upon increased fuel economy, fewer starts and stops of boilers, superior heat load prediction, and customer's opportunity to influence energy invoice. In order to exploit the full potential, reliable dynamic prices for DHC need to be produced, smart measuring devices to the buildings of interest should be extended, and an interactive optimization cloud service should be developed. The thesis focused on utilizing big data from heavy mass buildings constructed between 1980 and 1990. Because these buildings possess a high thermal inertia, they were utilized as sensible short-term TES.

The main objective of this thesis was to present the effects of DSM on a DH system with two simulation models. These models incorporated a VPP platform in which DSM actions were allocated. The target was to distinguish cost savings for both DH producer and customer. For this purpose, two different simulation algorithms have been created: the first one utilized existing load profiles in order to create an artificial DH system. 15% of the building dataset was optimized based on dynamic price signals. The optimized heat load of each virtual building unit accounted 40-70% of the total heat load, since the rest was assumed to be designated for ventilation and DHW. In the simulation, loads were shifted from expensive price hours to inexpensive hours, and no energy conservation is implemented. The customer is able to extend cost reductions by changing DSM configurations, such as reference temperature set points and upper and lower temperature boundaries. The simulation concluded that variable heating costs can be reduced by 11% in heavy mass buildings during the heating season. However, as the variable costs count approximately one fourth of the total DH price, the economic gain remains low.

By including 15% of the building stock's heated floor area within DSM, a sufficient amount of the peak loads could be reduced and shifted to off-peak hours. Furthermore, the CHP plant could operate with a steady maximum load in the majority of time. By more than 60%, the simulated system overreacted on the price signals which resulted in deep load drops and unrealistic share of night time heating. The simulation used at the end office buildings, commercial premises, and industrial buildings for DSM events. It turned out that residential buildings were not likewise suitable for load control, since the occupancy was harder to predict and the load curve peaked at different time than in the whole system. Nonetheless, by having a sufficient amount of various building types, the producer can rely on the flexibility of the buildings and view them as a virtual thermal storage system. The heat producer is able to decrease variable production costs during the heating season by 1.1 €/MWh, which equals to 6% of the total variable costs through DSM. Furthermore, more than 40% of the oil boiler start-ups could be mitigated during a year.

The second simulation shifted space heating loads of individual rooms based on external price signals. The objective function within the MPC model combined optimal storage control with a thermal comfort penalty. By this, the thermal comfort level of occupants can be sustained and measured while loads were shifted. The model utilized an ANN algorithm as a black box with input factors, such as short-term weather forecasts, occupancy pattern, and neighboring room temperature. Initially, this algorithm can be utilized for energy conservation. By adding a relative price variable to the function, the virtual building storage unit optimized consumption based on total system costs and therefore performed DSM. The significance of weighting factors has been pointed out, since they determine the importance of consumer comfort versus shifted energy.

DHC producers can benefit from the flexibility of demand and thus decrease cost pressures. Depending on the structure of the DHC system, producers can optimize load on either electricity or heating prices. When a sufficiently large share of buildings is participating in DSM, DHC providers can even postpone investment decisions on additional heat generation capacity. The estimations provided in this thesis indicate that if predictive DSM is largely implemented in all office buildings, commercial premises, and industrial buildings constructed only between 1960 and 2000 in Finland, it would offer a thermal energy storage capacity 28.8 million m^2. With dynamic pricing, the total potential could range between 10% and 25% of peak demand or 700–1700 MW. These depend on the actual storage capacity, the building stock, the DHC system, and whether dynamic pricing is deployed on an opt-in or opt-out basis.

As the cost savings are accumulating on the producer side, DSM investment incentives should come from the producer side and models for sufficient compensation should be created. One way of securing energy delivery to the customer and effective plant operation for the producer is to add a third party operator to the system. This operator would forecast building consumption and realize DSM actions with control devices. This party would also allocate the targeted load shifting amount among the buildings in the most cost effective manner by an agent-based auction system. It has been pointed out that without regulation it is hard to convince the consumer to trust the third party operator or the DHC company. Additionally, regulation and standardization could accelerate development and investment decisions.

With the current trends of digitization, energy efficiency in buildings, variable electricity prices, urbanization, and customer integration, investing in measurement and control devices advances. Therefore, predictive DSM in DHC systems in connection with intelligent control devices can lead to cost avoidance in heating and cooling generation. With the proper alignment of technology, pricing, and incentives, DSM has potential to play a key role in the value proposition for the grid of the future.

7.3 Limitations

In this section, a summary of limitations of the thesis are provided to point out major topics for further research. First, the results presented in the thesis depend for instance on the used fuels, as seen in the CO_2 emission results. Additionally, the shape of the demand curve overrated the impact of other clusters than residential buildings, which is not the case in a typical Finnish building stock. DSM results depend also on grid control, policy on generation planning, and degree of building TES capacity. Additionally, the simulation based on Helsinki's outside temperature data for the year 2015, which was exceptionally warm. Therefore, testing the model on temperature data from different years could bring more confidence in the results. A throughout sensitivity analysis would bring further reliability on the estimations.

In this thesis, the change heat demand and inside temperature was approximated as a black box with input and output parameters. This has been justified because each building unit behaves in a different manner and precise building models were beyond the research scope. In order to verify the accuracy of the thermal conductivity in the room, progressive building and system models, such as TRNSYS, IDA-ICE or EnergyPro should be used for comparison.

On the other hand, the second simulation model starts at the situation when the algorithm has learned already the room performance. Training time estimations and reliability are not verified. The reader might ask, why the heat balance of buildings is studied in depth, if the ANN algorithm functions as a black box. This can be justified by arguing that the weighting factors cannot be set without understanding the logic behind the toolbox. The ANN approximation does not give any information about the shape of the function it is describing and thus the "black box" needs to be opened at least for a "gray box". Another issue on the ANN algorithm is the time consumption of the training session. The machine learning algorithm of the control device demands time for increasing prediction accuracy. The results of the thesis are based on simulations in an ideal environment. The next step is to put predictive DSM operations into practice by piloting first individual buildings and after that connecting the building stock for DSM auctions. This is further discussed in the upcoming section.

7.4 Future Research

Developing novel pricing schemes which comprise DSM actions has been pointed out to be an essential factor for applying DSM. For this, standards and regulations would enable a fast development for load control in Finland. However, consensus between stakeholders can be found by determining factors which provide acceptable value in real case studies. Furthermore, by utilizing the prediction tool described in this thesis, the amount of value can be investigated accurately on time. Based on the difficulties of contracting power between energy providers and customers, novel business models could emerge, such as DSM operators as ESCOs. On the other hand, DHC producers have also an opportunity to create new value for their matured business. Therefore, further research on comprehensive business models should be carried out.

In a future smart grid system, where electricity grid and DHC grid are interactively combined, an optimal resource allocation method can be developed. Excess electricity can be converted to heat via centered heat pumps or even direct electric resistances. Alternatively, buildings can be equipped with heat pumps which optimize DHC and electricity consumption based on the system price of both mediums. Even though the hourly pricing scheme and regulation has not yet been developed, the technology for optimal system balancing already exists. In this thesis, the simulation calculated marginal costs for the next day. In further projects, marginal costs and the DSM operation could be predicted a few days in advance.

The first optimization algorithm, which aims to shift loads to the most inexpensive hours without reducing energy consumption, could be simulated with an existing DHC system. By this, a realistic case study with accurate conclusions could be drawn. Estimations on long-term investment savings could be in this way realized. Also, real variable pricing applications, whether they are hourly or stepwise based, could be implemented in order to assess the real value of DSM to a local system. Additionally, a simulation for DSM in a DC system could offer entire new study data.

Actual pilot programs should be conducted for testing the two-side communication between DHC producer and the buildings with DSM potential. This could be first tested among the largest DH customers within a DHC system in order to verify simulation results. Since a diverse building stock empowers the system to achieve cost savings more effectively, the operation field can be after the verification extended to larger group of buildings. This group could be managed with a smart auction system which independently strives for the least possible costs. The producer treats the separate energy storage units in buildings as one energy storage with a VPP platform. By this, the small scale model presented in the thesis could be verified and extended to real world DHC systems. The piloting phase should investigate in addition to technical and economic benefits also the social aspects, such as the attitude and behavioural change of the end users.

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Legislation

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Laki sähkön ja eräiden polttoaineiden valmisteverosta 30.12.1996/1260.

List of Appendices

Appendix 1: Standard usage of buildings (Kurnitski 2009), Standard reference temperatures in residential buildings (Motiva 2014, BTU 2008), and standard reference temperatures in building types (BTU 2008).

Building type	Usage time			Target temperature		Utilization rate	Lighting [W/ m^2]	Devices [W/ m^2]	Human [W/ m^2]	Person density [pp/m^2]
	Time	h/24h	d/7d	When occupied	When unoccupied					
Residential building	00:00-24:00	24	7	19-23	16	0.6	11	4	3	1/28
Office building	7:30-18:30	11	5	19-23	16	0.65	12	12	5	1/17
Commercial premise	8:00-21:00	13	6	19-23	16	1	19	1	2	1/43
Public building	8:00-18:00	10	5	19-23	16	0.6	18	6	14	1/5
Exercise hall	8:00-22:00	14	7	17-19	16	0.5	12	1	5	1/17
Industrial buildings	8:00-18:00	10	5	17-19	16	0.5	12	6	5	1/17

Room type	**T_{ref} [˚C]**
Living room	20-21
Bedroom	18-20
Bathroom	22-24
WC	18-21
Kitchen	18-21
Corridor	15-18
Staircase	10-18

	Residential buildings	Office buildings	Industrial buildings	Commercal premises
Occupancy [˚C]	19-23	19-21	17-19	19-21
Non-occupancy [˚C]	16-18	16-18	15-17	16-18

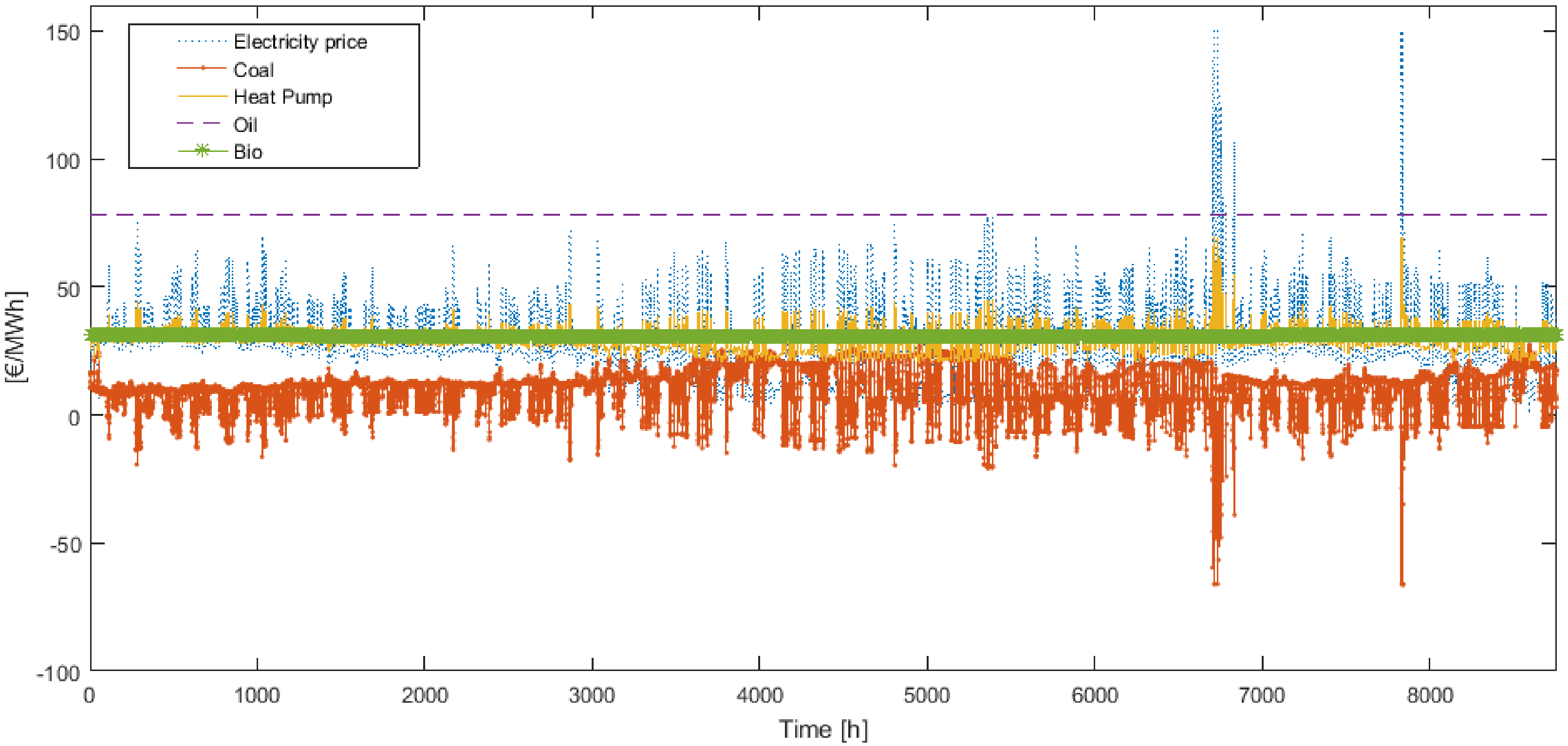
Appendix 2: Estimated factors for generation costs. (IEA 2010, Statistics Finland 2016, Customs 2016, Nord Pool Spot 2016a, Energy Authority 2016)

Power Plant	Fuel prices €/MWh$_{fuel}$	Fuel efficiency	O&M €/MWh$_{fuel}$	Tax €/MWh$_{th}$	Emission allowance[20] €/MWh$_{fuel}$	Operation time h
Coal CHP	10	0.9	5	12.54+16	1.7	6000
Biomass HOB	22.5	0.87	5	0	0	5000
Oil HOB	42	0.9	5	22.2	1.4	3000

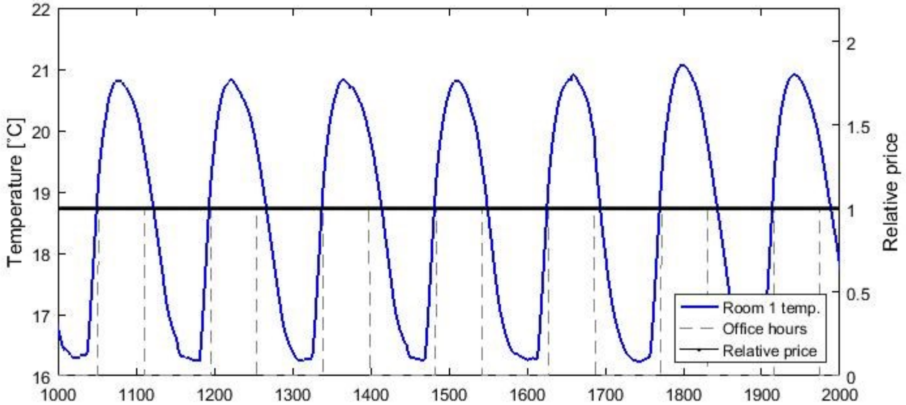
	Electricity price €/MWh	Transmission costs €/MWh	Electricity tax €/MWh	O&M €/MWh	COP
Heat pump	0.32-150.06	30.4	22.53	1	3

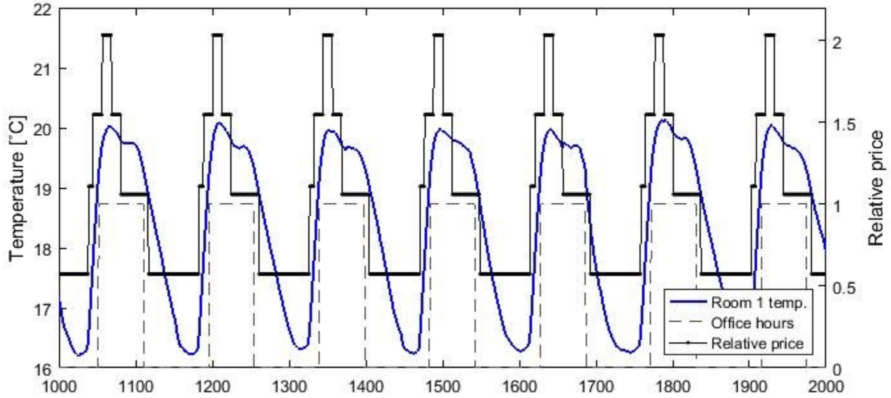
20 EUAs are calculated based on the specific CO_2 emission rate of the fuel and with a EUA price of 5 €/tCO_2e.

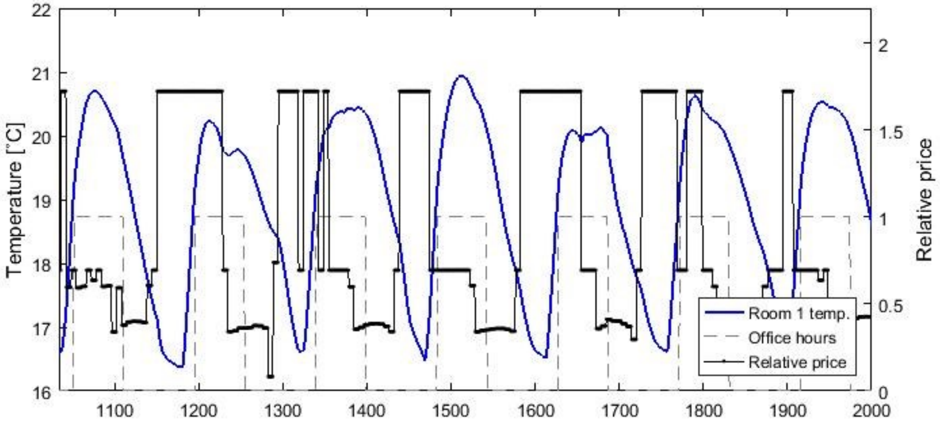
Appendix 3: Variable costs of generating DH for various fuels and electricity spot price during 2015.



Appendix 4: Indoor temperature change with steady, stepwise, and hourly changing relative DH price.







Appendix 5: Original load profile (upper graphic) and optimized load profile (lower graphic) for the entire year of 2015 in a simulated DHC system.