FACULTY OF TECHNOLOGY

SENSITIVITY ANALYSIS FOR MULTI-OBJECTIVE OPTIMIZATION WEIGHTS IN ENERGY SYSTEMS

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ABSTRACT

Sensitivity analysis for multi-objective optimization weights in energy systems

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Supervisors at the university: Jari Ruuska, Mika Ruusunen, and Petri Hietaharju

This master's thesis dealt with the production of district heating, the popularity of which is growing due to its low-cost production and environmental friendliness. In the experimental part, multi-objective optimization of district heating production and its consumption was considered. The aim was to maximize profits and minimize emissions on the production side by identifying the optimal weights for the presented objective function. In addition to this, a study was made of how the integration of heat pumps into the district heating network affected the emissions and profits of the production plant.

The multi-objective optimization of the experimental part was simulated using MATLAB® software. The prediction horizon was two days (48 hours). The study focused on tuning parameters in the determined objective function, namely weights for profits and emissions. Simulation scenarios included high and low electricity prices and different numbers of heat pumps. The theory part of the master's thesis introduced the energy systems of the future and how they can be turned into more sustainable solutions.

Based on the results of multi-objective optimization, it can be concluded that there is no single optimal solution that would suit every situation, regardless of the electricity price and the number of heat pumps. However, when comparing all the results, it can be noted that when more heat pumps are integrated into the district heating network, the profits tend to increase and emissions decrease during periods of low and high electricity prices.

Keywords: district heat, multi-objective optimization, smart energy systems

TIIVISTELMÄ

Herkkyysanalyysi energiajärjestelmien monitavoiteoptimoinnin painokertoimille

Nadja Åman

Oulun yliopisto, prosessitekniikan tutkinto-ohjelma

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Tämä diplomityö käsitteli kaukolämmön tuotantoa, jonka suosio on kasvamassa sen edullisen tuotannon ja ympäristöystävällisyyden vuoksi. Kokeellisessa osassa simuloitiin monitavoiteoptimointia Oulun kaupungin lämmöntuotantolaitokselle sekä kaupungin rakennuksille. Tavoitteena oli maksimoida tuotantolaitoksen tulos sekä minimoida päästöt määrittämällä esitetylle kustannusfunktiolle optimaaliset parametrit. Tämän lisäksi simuloinneilla tutkittiin, miten lämpöpumppujen integrointi osaksi kaukolämpöverkkoa vaikuttaa tuotantolaitoksen päästöihin sekä tulokseen.

Kokeellisen osan monitavoiteoptimointi simuloitiin MATLAB® ohjelmistotyökalun avulla. Ennustehorisonttina oli kaksi vuorokautta eli 48 tuntia. Työssä keskityttiin määrittämään optimaaliset painokertoimet taloudellinen tulos- ja tuotannon päästöt -muuttujille kustannusfunktiossa. Simulointiskenaarioissa muuttuvina tekijöinä olivat sähkön hinta sekä lämpöpumppujen määrä. Tämän lisäksi verrattiin kalliin ja edullisen sähkönhinnan vaikutusta tuotannon tulokseen sekä päästöihin. Diplomityön teoriaosuudessa tutustuttiin tulevaisuuden energiajärjestelmiin, ja siihen miten niistä voidaan tehdä kestävämpiä.

Monitavoiteoptimoinnista saatujen tulosten perusteella voidaan todeta, että yhtä optimaalista ratkaisua ei saada, joka sopisi jokaiseen tilanteeseen sähkönhinnasta ja lämpöpumppujen määrästä huolimatta. Kuitenkin kaikkia tuloksia verrattaessa voidaan todeta, että mitä enemmän lämpöpumppuja on integroituna kaukolämpöverkkoon, sitä suurempi on tulos. Tämän lisäksi myös päästöjen kokonaismäärä näyttää laskevan kaupunkitasolla.

Asiasanat: kaukolämpö, monitavoiteoptimointi, älykkäät energiajärjestelmät

FOREWORD

This master's thesis was carried out in the Control Engineering group, which is part of the Environmental and Chemical Engineering Research Unit of the University of Oulu. The topic of the thesis was part of the Highly Optimized Energy Systems (HOPE) project. The HOPE project aims to find solutions and tools that can improve the energy efficiency of future energy systems. In this master’s thesis, multi-objective optimization was carried out for a district heating network.

I would like to thank my thesis supervisors Jari Ruuska, Mika Ruusunen and Petri Hietaharju, for giving me the opportunity to work on the HOPE project. They also provided excellent guidance at different stages of the project. Especially, I would like to thank Petri Hietaharju for his assistance with the experimental part of my thesis.

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LIST OF ABBREVIATIONS

3GDH	Third-generation district heating
4GDH	Fourth-generation district heating
5GDHC	Fifth-generation district heating and cooling
AC	Alternating current
CHP	Combined heat and power
DC	Direct current
DH	District heating
DHC	District heating and cooling
DHS	District heating system
DM	Decision maker
DSM	Demand side management
EV	Electric vehicle
HOB	Heat-only boiler plants
HP	Heat pumps
INLP	Integral non-linear programming
LP	Linear programming
MES	Multi-energy system
MILP	Mixed-integer linear programming
MINLP	Mixed-integer nonlinear programming
MOO	Multi-objective optimization
MOOA	Multi-objective optimization algorithm
MOOP	Multi-objective optimization problem
NLP	Non-linear programming
SC	Sector coupling
STD	Standard deviation
TAC	Toxic air contaminant

1 INTRODUCTION

The world's energy demand is constantly increasing. In the modern world, many machines, bicycles and cars are powered by electricity. The growing number of electricity and energy consumers and their increasing energy needs raises the issue of how to meet the growing demand for energy in an environmentally friendly manner.

As a result, energy systems such as electricity networks and district heating networks are changing to become smarter and more sustainable. It is necessary for energy systems to meet certain criteria to be considered smart and sustainable. These criteria include the use of sufficient, affordable, reliable and clean technologies and resources. This master's thesis explores how smart energy systems differ from current energy systems.

In the thesis work, multi-objective optimization simulations of Oulu's district heating system were performed. The aim was to maximize profits and minimize emissions on the production side by identifying the optimal weights for the presented objective function. In addition to this, a study was made of how the integration of heat pumps into the district heating network affected the emissions and profits of the production plant.

This thesis is part of the Highly Optimized Energy Systems (HOPE) project. HOPE is a project that supports industry players in developing solutions to improve energy efficiency in energy networks. The research goal of the HOPE project is to develop tools and solutions for the multi-objective optimization of energy systems.

2 ENERGY SYSTEMS

Energy systems are designed to produce energy for the customer, for example in the form of electricity or heat. Electricity and district heating networks are the main energy distribution networks.

Our society's reliance on energy systems has increased rapidly in recent years, which has increased concerns about the future of energy production. Moreover, energy production increases carbon dioxide (CO_2) emissions significantly.

In other words, as the need for energy grows, so does the environmental impact. Therefore, efforts are being made to reduce the use of fossil fuels while increasing use of renewable fuels. This section introduces the terms electricity, district heating, sector coupling, smart grid and prosumer. (Siddiqui & Dincer 2021)

2.1 Electricity

Electricity is an essential part of modern life. It is used to perform many functions every day, such as the lighting, heating and cooling of homes and the operation of various kinds of electrical equipment. Electricity is used in several areas, including the home, community safety and medical care. Also, it is used in agriculture, transportation, entertainment, social interaction and industrial development. (The Scientific World 2020)

Electricity is produced in power plants and supplied to consumers through a complex network. This network consists of substations, transformers and electricity lines connecting electricity producers and consumers. (EIA 2022)

Figure 1 shows a traditional electricity network system. Different voltage power lines converge at substations, which are responsible for converting and distributing electricity to consumers. Substations reduce the high transmission voltage of electricity to a low voltage that is suitable for users. The lowest voltages of up to one kilovolt are called low voltages, higher tensions of 1–36 kilovolts are called medium voltages, and 110–400 kilovolts are high voltage. (Finnish Energy 2022)

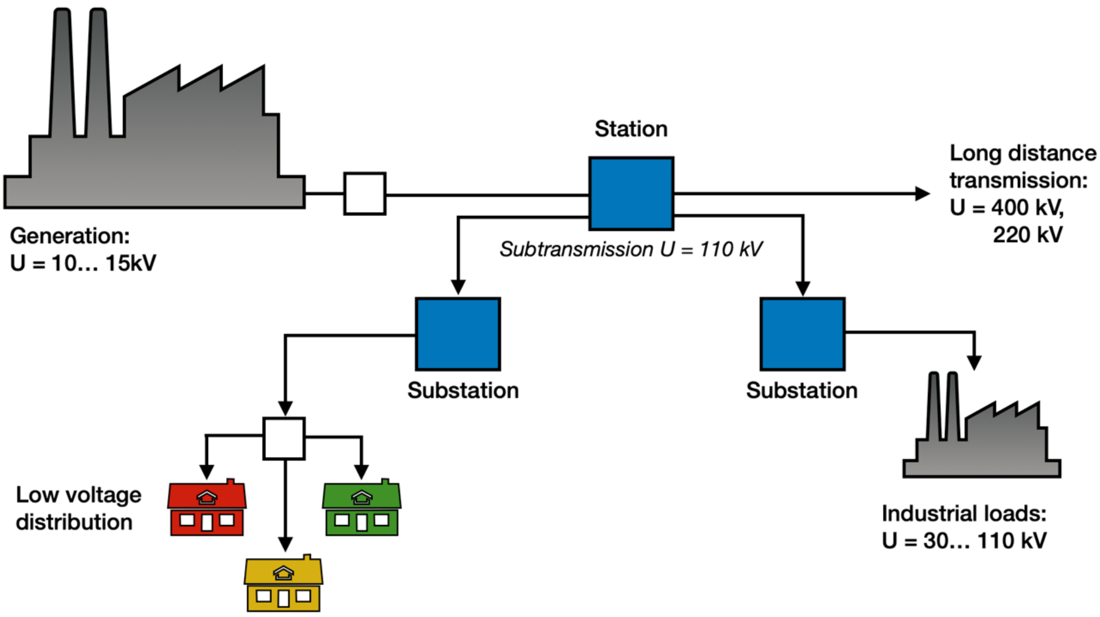

Figure 1. Traditional electricity network system (retelling Delfino et al. 2018, p. 3).

2.1.1 Production

Electricity is a secondary energy source, meaning it must be produced by converting primary energy sources, such as coal, natural gas, biogas, or solar energy (EIA 2022). The primary energy source, for example coal, can be combusted to vaporize water. The resulting steam spins a turbine, and the turbine spins a generator, which generates electricity (Figure 2). (STEK 2022a; STEK 2022b)

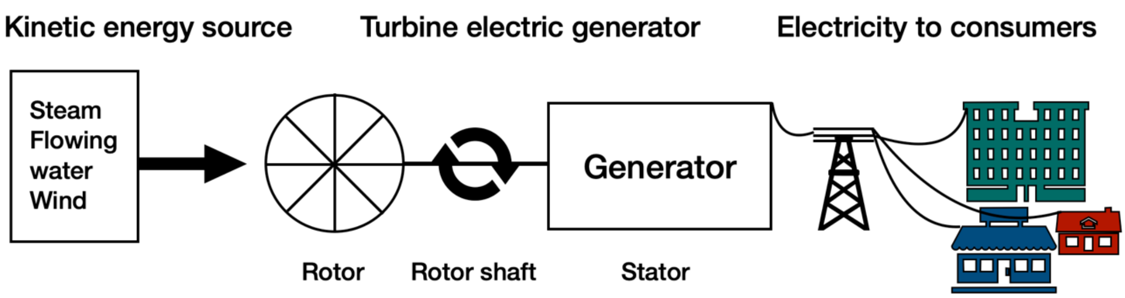

Figure 2. Electricity generation (retelling EIA 2022).

Electricity is generated in power stations, which differ in terms of their operating power. In a hydroelectric power station, the movement of the water serves as the driving force for the turbine, for example, the flow of rapids or a waterfall. In a wind power plant, the wind generator is turned by the wind's kinetic energy, and in a thermal power station, the heat energy of steam spins the turbines. (STEK 2022a; STEK 2022b)

In simple terms, electricity generation is the result of the interaction between magnetism and electricity. When a wire or other conductive material moves over a magnetic field, the conductor generates electrical current. (EIA 2022)

To combat climate change, global changes have been made in electricity generation to enable the rapid electrification of end uses in transportation, housing and industry. With electrification, the electricity demand will increase enormously, as will the need to generate as much of it from renewable and sustainable sources as possible. (IEA 2022)

In 2020, renewable energy sources produced 37% of all electricity generated in Europe. Wind power accounted for 36% and hydropower 33%, solar power share accounted for 14%, the share of solid biofuels was 8%, and other renewable sources accounted for 8%. (Eurostat 2022)

Solar power is the fastest-growing source of energy in Europe (Eurostat 2022). However, its popularity is growing in other countries as well. Solar energy is the fastest growing and the most affordable source of electricity in America. More than three million solar energy plants have been built, including one million in the last two years. The popularity of solar energy is on the rise because the amount of sunlight that the surface of the earth receives in an hour and a half is enough to meet the world's energy needs for one year if it could all be collected. (Energy.gov 2022b; Energy.gov 2022c)

Electricity can be generated for consumers in two ways. One is called centralized generation and the other decentralized generation. Centralized electricity generation is driven by the power stations. The electricity is delivered to consumers such as businesses and real estate by power lines and cables. Centralized electricity generation is considered as a reliable, consistent and in many cases easier solution because it is an established system. The centralized electricity generation model has served for decades. (Peak 2022)

In decentralized electricity generation, electricity is obtained from several sources that are spatially distributed. This means that when one power line breaks or there are problems in a power plant, electricity generation does not stop, as there are other sources of electricity. (Peak 2022)

Decentralized electricity generation is becoming more popular in the electricity market for a variety of reasons, including climate protection. In decentralized electricity generation, electricity is only transported over short distances, which reduces transport losses. Likewise, CO_2 emissions are reduced because decentralized power stations can typically be run on gas or renewables, whereas coal-fired power stations are commonly used in large-scale centralized electricity generation. (Karger & Hennings 2009)

2.1.2 Network

The electricity network is one of the world's largest, most complex and most advanced systems. However, globally, electricity networks are outdated and need to be more sustainable. Thousands of people are without power for a few hours each day due to their current electricity grid, even in industrialized countries. Electricity networks can of course be made more durable, for example by replacing overhead cables with underground cables. (Ensto 2018; Zahedi 2018)

Electricity networks include production, transmission and distribution. In other words, electricity is produced by a generator for consumers, for industrial, commercial or residential use. Electricity is transferred from production plants to consumers via a high-voltage (transmission) and low-voltage (distribution) system through wires, transformers, switches and other electrical equipment. (Vassalo 2015)

The substations in the electricity network can usually be divided into three main types according to their voltage levels. These main types are transmission substations, sub-transmissions substation and distribution substations. Transmission substations operate at a voltage level of 138 kV or more. Sub-transmission substations operate at a voltage level of 33–138 kV and distribution substations operate at the lowest voltage level of 0.4–11 kV. (Csanyi 2019)

Electricity networks are without natural storage capacity, which means energy cannot be stored in the electricity network itself. This means that when the demand changes, so does the load. In this case, the generators must be adjusted to meet the demand. However, electricity can be stored in electricity storage facilities, for example in batteries. (Vassalo 2015)

There are two types of electrical current running in the mains: alternating current (AC) and direct current (DC). The main difference between these is the movement of electrons. In DC, electrons flow in only one direction, forwards. On the other hand, in AC, electrons move in both directions, positive and negative. Another difference between AC and DC is that AC is produced in electric power plants while DC is related to batteries and solar panels. (Accuenergy 2022)

AC is the most rational option for supplying an electric current over long distances, and for this reason, AC electricity is produced worldwide. This is because if efforts are made to transfer power efficiently over long distances, the voltage level must be very high, commonly hundreds of thousands of volts. A large voltage allows a large amount of power to be transferred with a smaller current, so that less power is lost during the transfer. DC electricity is only used in some transmission routes due to its cost and inefficiency. (Accuenergy 2022; Vassalo 2015)

Electrical equipment depends on DC. In many devices, such as phones and computers, integrated circuits consisting of transistors and other components require DC voltage to function. This is because AC can easily damage sensitive components due to the large voltage. (Accuenergy 2022)

Electricity that is transported over long distances is converted from DC to AC in substations. This conversion is usually made close to consumers to minimize electricity losses. Once the electricity has been converted to DC, the electrical equipment receives the DC voltage it needs to operate. During transport, electrical energy can flow through several substations between the power plant and the consumer, and the voltage can be changed in several stages. (Csanyi 2019)

2.1.3 Finnish Electricity Network

The electricity network of Finland consists of the main grid, high-voltage distribution networks and distribution networks. The main grid in Finland consists of over 15 000 kilometers of power lines. To reduce transmission losses, the voltage of the main grid can be divided into three different sizes: 400 kilovolts, 220 kilovolts and 110 kilovolts. The network provides maximum transmission power, long-distance connections and high transmission voltages. (Finnish Energy 2022)

The electricity network continues from the main grid to high-voltage distribution networks that transfer electricity regionally. Distribution networks are the third part of the electricity grid, which can access the main grid either through a high-voltage network or directly. The main difference between a high-voltage distribution network and a distribution network is that the high-voltage distribution network operates at a voltage of at least 110 kilovolts, in contrast to a distribution network that operates at 20, 10, 1 or 0.4 kilovolts. (Finnish Energy 2022)

The consumers' homes receive electricity from distribution substations that are connected to distribution networks. However, industry, trade, services and agriculture, which use more electricity, can be connected either to a distribution network, high voltage distribution network or directly to the main grid. (Finnish Energy 2022)

2.1.4 Consumption

There have been major changes in electricity consumption over the past decades. In general, global electricity consumption has been rising steadily. Global electricity consumption has grown by several percent every year, for example, by 3.1% in 2018. Global electricity consumption temporarily dropped by 1.1% in 2020 due to the COVID-19 virus but has now risen again. (Rahman 2020; Enerdata 2022)

There are many different uses for electricity. It is used in homes, for example, for boiling water, for TV and radio, for computer use, and for heating and cooling the home. Community safety is provided by outdoor lighting, alarm systems and traffic lights, all which are powered by electricity. Electricity is also required for electrotherapy equipment, surgical equipment and CT scanning equipment for medical use. It also plays an important role in electrical machines and automation, which are used in industry and commerce, for example, in lifts and escalators. The use of electricity is also necessary for electric milking machines, irrigation systems, transportation such as electric vehicles, and human interaction such as telephone communication over long distances. (Electrical Technology 2022; The Scientific World 2020)

Many of the devices that people use in their daily lives are now powered by electricity. Lawn mowers used to be operated manually, but today there are robotic lawn mowers powered by electricity. Also, the number of electric vehicles (EVs) has increased over the past ten years. In 2011, about 50 000 EVs were sold worldwide. In 2021, the number of EVs sold was 4.6 million and it was estimated that this figure would double by 2022. This would mean ten million cars that all need electricity to operate. (IEA 2020b; Barrera 2022)

When oil prices rose, this had a major impact on the purchase of electric vehicles. Now, electric vehicles are so popular that the waiting list for them is at least six months. By the end of 2022, it had been estimated that over ten million electric vehicles would have been sold. (CNBC 2022; McKerracher 2022)

As electricity demand increases, its price rises as well. Electricity demand is not constant and can sometimes fluctuate wildly due to sudden weather changes, cable damage or other factors. In extreme cases, big changes in electricity demand can even cause blackouts. The proposed solution to this problem is demand-side management (DSM). DSM means shifting the use of electricity from hours of high consumption and high prices to a more favorable time. DSM is growing as the amount of inflexible production in the grid, such as nuclear power or renewable energy, increases. (Enel 2022; Fingrid 2022b)

DSM provides consumers with the opportunity to reduce and transfer electricity use from peak times through time-based prices and other economic incentives. Incentives to engage customers to use DSM includes providing time-based prices. These include uptime pricing, critical peak pricing, changing peak pricing, real-time pricing and critical top discounts. Smart customer systems, such as home screens or home networks, can make it easier for consumers to monitor their electricity usage. These programs also have the potential to help power generators save money by reducing peak demand and the ability to defer new power station and electricity distribution systems. (Energy.gov 2022a)

The electricity industry considers DSM programs as an increasingly valuable resource option. For example, sensors can detect peak load problems and use an automatic switch to control or reduce power in strategic locations; this is used to eliminate the possibility of overload and the resulting power outage. (Energy.gov 2022a)

2.2 District heating

District heating (DH) is the most common form of heating in Finland, since 45% of residential and public buildings are heated by DH. In addition to this, it is the most popular heating method among new properties. More than 50% of new properties are heated with DH. (Energiateollisuus 2022a)

Even though DH is the most common form of heating in Finland, it produces only a small percentage of the heat needed to heat buildings globally. Since the year 2000, the global consumption of DH has remained constant at 8.5%. However, the popularity of DH has started to rise over the past couple of years, especially in China, where the share of DH rose from around 24% to 30% over five years. (IEA 2020a; IEA 2021)

Most DH is produced in Russia and China. The production of DH in China has tripled in the last 20 years. In Russia, production has decreased slightly, but it still produces a large part of DH. The main producers of DH, in addition to China and Russia, are Europe and the United States. (IEA 2021)

Hot water is transferred through the DH network to the customer’s heating substation. The heating substation transfers the heat from the DH network to the consumer’s heating system, such as radiators or ventilation, via heat exchangers. A traditional DH network is shown in Figure 3. (Gebwell 2022)

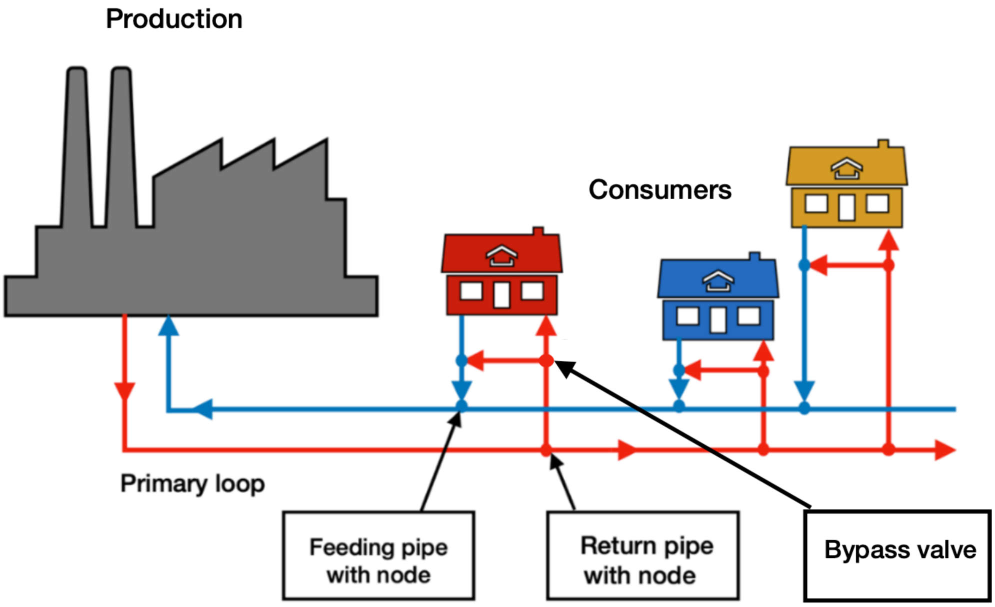

Figure 3. Traditional DH system (retelling Gambarotta et al. 2017).

A district heating system (DHS) produces electricity, heat and cooling for local buildings. As a result, it enables, among other things, the reduction of transmission losses in on-site production, utilization of waste heat, reduction of emission problems, utilization of renewable energy sources and a decrease in the need for large production facilities. (Sameti & Haghighat 2017)

A DHS consists of three parts, which are shown in Figure 4. These are heating plants, distribution networks and end users. In a DHS, heat suppliers must constantly meet the needs of the end user. Since the amount of heat demand varies, there are two types of heating plants: permanent, where the heat production constantly exceeds the heat demand of the network, and non-permanent, where the heat production varies over time. (Sarbu et al. 2019)

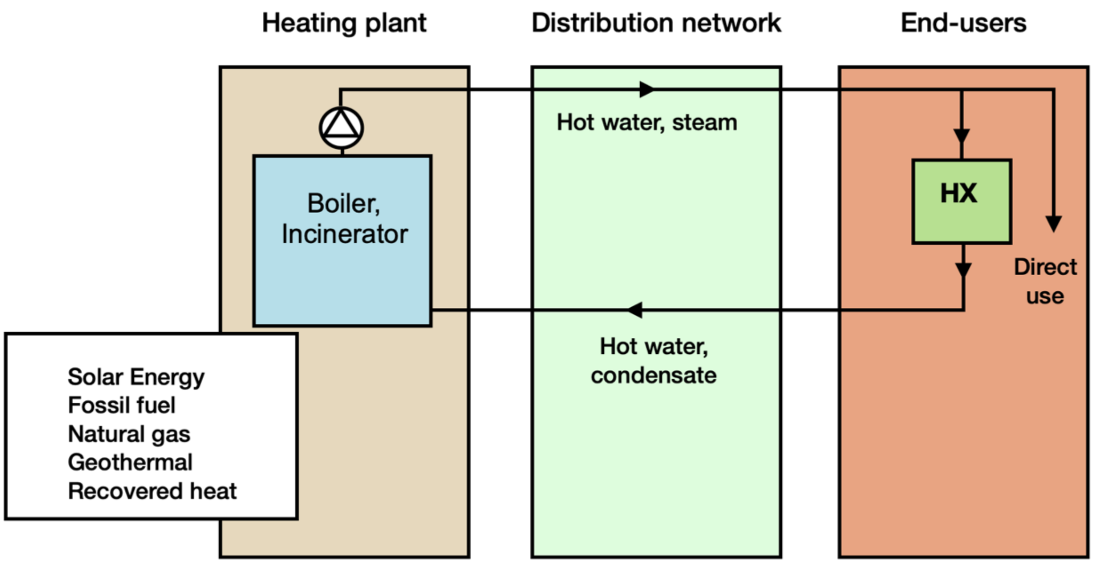

Figure 4. Main components of a DHS (retelling Sarbu et al. 2019).

2.2.1 Production

DH can be produced in many ways. In Finland, DH is produced typically in cogeneration power stations (the production of electricity and heat) and in separate heating plants. During cogeneration, also known as combined heat and power (CHP), the waste heat from the turbines to produce electricity is recovered and used for heating. In addition, the production of DH utilizes various waste heat generated in cities and industry. (Kaukolämpö.fi 2022; Motiva 2022)

The most common fuels for DH production in Finland are wood-based fuels, such as pellets and wood chips. Natural gas, coal, biogas and peat are also used as fuel for DH. (Energiateollisuus 2022a)

The efficient production of DH, especially CHP production, reduces the environmental burden and climate impacts. Cogeneration is twice as efficient as the separate production of electricity and heat. The energy efficiency of a simple heating plant can be 20–35%, while the energy efficiency of a CHP plant can be almost 80%. (Sarbu et al. 2019; Kaukolämpö.fi 2022)

In Finland, CHP production generates one-third of electricity. In contrast, in the European Union's 27 member states CHP production accounts for only 10% of all electricity production (Energiateollisuus 2022b; European Union 2021).

Data collected by Finnish Energy is used to produce statistical publications on DH. These publications show how much heat is generated each year, for instance. DH production in 2020 was 33.6 TWh in total, and this figure increased by 17% in 2021, namely 39.3 TWh. (Energiateollisuus 2022a)

The popularity of climate-neutral district heating has been increasing for several years, and in 2021 it exceeded 50% of the total district heating production. District heating is constantly being developed to become more environmentally friendly. According to statistics for 2021, the use of renewable fuels doubled, and the share of waste heat even tripled compared with the results from ten years ago. In addition, district heating emissions have been reduced by 38% over ten years. (Energiateollisuus 2022a)

District heating companies highlight the development of environmental protection in their environmental reports, which are published as separate reports from the annual reports (Kaukolämpö.fi 2022). In addition, the aim is to measure environmental emissions through continuous measurements of air quality. Compared with other heating plants, district heating plants have highly developed pollution monitoring equipment to reduce the emissions of hazardous compounds. (Danfoss 2022a)

2.2.2 Network

Consumers receive DH in their buildings from plant that produces district heating, which is pumped as hot water to consumers through two-pipe underground heating networks. DH pipes are installed at a depth of 0.5–1 metre in the ground under pavements, streets, parklands and bike paths. Large DH pipes can also be installed in tunnels. (Danfoss 2022a; Energiateollisuus 2022c)

Water flows through the pipes of the DH system thanks to hydronic balancing. A hydronic balance is the process of equalizing pressure in a building's hydrological heating or cooling system to optimize water distribution. Achieving an optimal indoor climate result in minimal operating costs and maximum energy efficiency. (Danfoss 2022b)

2.2.3 Consumption

DH produces heating energy for residential and public buildings. Finland currently has 309 municipalities (Kuntaliitto 2022). In total, 166 of these have a district heating system. Therefore, it is the most common form of heating in Finland. The amount of energy produced and consumed each year is also high. (Motiva 2022)

Using DH for heating is simple and trouble-free for the consumer. By using remotely readable meters, the consumer does not have to report the consumption figures themselves. Oulun Energia, for example, offers a free online service called "Energy Account" which allows consumers to see their consumption data, electricity network and DH contract information, as well as their DH and transmission bills. (Oulun Energia 2022a)

Consumers can reduce the energy consumption, costs and emissions of their properties by using demand-side management (DSM) in the DH network. The most significant benefits are derived from regulating peak power and reducing consumption peaks. (Caverion 2022)

These benefits of DSM can be achieved, for example, by reducing the use of peak boilers during short load peaks. In addition, DSM strategy encourages DH companies to cooperate with customers at times when there are significant risks to DH operations. To maximize the benefits of DH in DSM, the DH company will give a signal to the properties connected to the system that they should take steps to reduce their demand for DH capacity. According to DH companies, DSM can save 1–3% of annual heat production costs. (Sirola 2015)

2.2.4 Third-, fourth- and fifth-generation district heating networks

In 2016, the International Energy Agency estimated that the global cooling demand of the residential and service sectors would triple, and that heat demand would decrease by 20–30% by 2050. In countries with hot, humid climates, district cooling solutions are becoming more popular, but their implementation is not yet widespread. Current DH networks are mainly third-generation systems (3GDH), whose high operating temperatures lead to significant distribution heat losses. For energy systems to meet the needs of the moment, they must be developed in a more sustainable direction. (Buffa et al. 2019; Nérot et al. 2021)

When the DH infrastructure moves from the current 3GDH to fourth-generation district heating (4GDH), the future benefits of the energy system will be lower network temperatures and integration with other energy sectors. There is currently a worldwide transition to carbon dioxide-free energy systems. To achieve a complete transition, all energy sectors must stop or reduce the use of coal, including the heating sector, which is responsible for the energy used for space heating and domestic hot water consumption. (Sorknæs et al. 2022)

The 4GDH system has been defined as a technological and operating model that promotes the development of sustainable energy systems. 4GDH systems enable the heat supply of low-energy buildings with low network losses when the use of low-temperature heat sources is integrated into the operation of smart energy systems. 4GDH technology can be used to smooth out excessive heat recovery and waste heat and increase the connection of renewable energy sources to the grid. (Lund et al. 2014; Buffa et al. 2019)

With the help of 4GDH technology, the aim is to provide a more sustainable heating system, but the same pipes in 4GDH systems cannot provide both heating and cooling services to different buildings at the same time. The solution to this challenge is fifth-generation district heating and cooling system (5GDHC) technology, which is still in the development phase. 5GDHC combines district heating and cooling (Figure 5). The difference between 5GDHC and 4DGH is that a 5GDHC system has two- or single-pipe systems that directly utilize the waste heat of the cooling loads. 4DGH does not offer this feature as it supplies and returns hot and chilled water separately. (Buffa et al. 2019; Von Rhein et al. 2019)

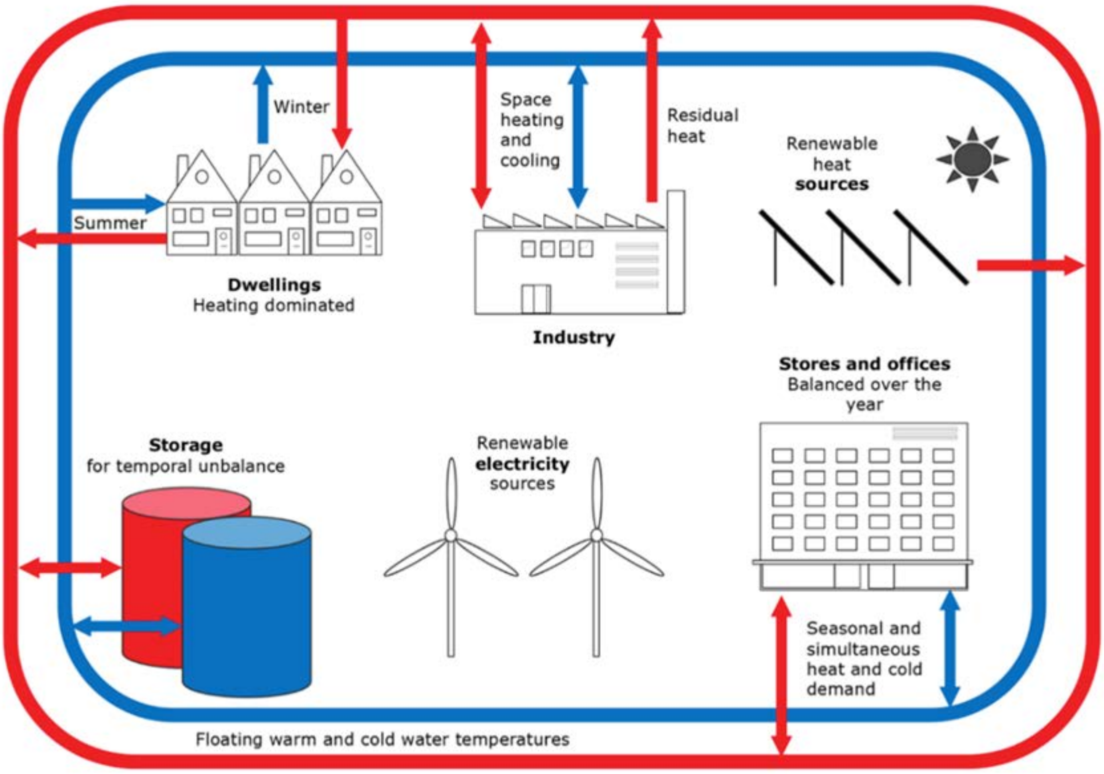

Figure 5. Fifth-generation district heating and cooling (under CC BY 4.0 license from Boesten et al. 2019).

Typically, fifth-generation district heating and cooling networks have input temperatures of 15–25 °C. As a result of this feature, it lessens heat losses and various low-temperature waste heat sources can be integrated. The ability of this system to absorb waste heat that cannot normally be recovered makes it an attractive solution for the future energy supply of urban areas. Therefore, 5GDHC technology is an integral part of the concept of smart heating networks. (Buffa et al. 2019; Von Rhein et al. 2019)

2.3 Smart energy systems

Energy provides the solution to many of the most crucial issues of the future, including climate change, sustainable development, health and the environment, as well as global energy and food security. However, traditional energy systems cannot meet the complex requirements of the 21st century. As a result, energy systems must be made smarter and more sustainable. (Dincer & Acar 2017)

To provide the flexibility needed for large and versatile renewable energy solutions, a smart energy system is designed to link energy sectors such as electricity, heating and transportation together. The transition from fossil fuels to renewable energy requires rethinking and redesigning of the entire energy system, including the production process and the consumption process. To achieve this, an intelligent energy system must have a range of infrastructures designed for different sectors of the energy system. Among them are smart grids, smart heating networks (district heating and cooling), smart gas networks and other fuel infrastructures. (Mathiesen et al. 2015)

To be considered smart and sustainable, energy systems must meet certain criteria. These criteria include the use of adequate, affordable, reliable, clean and 100% renewable technologies and resources. (Dincer & Acar 2017)

Smart energy systems go beyond smart grids and other similar terms. This is because smart grids focus mainly on the electricity sector, while smart energy systems are holistically focused on a greater number of sectors, such as electricity, heating, cooling, industry, buildings and transport. (Lund et al. 2017)

In a sense, smart energy systems are a huge entity made up of smaller individual parts, such as the smart grid, which focuses on one aspect of the smart energy system. There are also other smaller areas in smart energy systems, such as net zero energy buildings (NZEB), aimed at reducing household energy consumption and greenhouse gas emissions (GHG), and power to gas (P2G), which utilizes renewable electricity to produce hydrogen through water electrolysis. (Lund et al. 2017; Wei & Harrison 2021; Wulf et al. 2018)

2.3.1 Smart grid

The smart grid is a cutting-edge improvement on the traditional electricity grid of the 20th century. The goal of the traditional electricity network was to transfer power from a central generator to numerous users and customers. The smart grid is a technological change that describes the transition from an electrical network and electromechanically controlled system towards an intelligent, smart and electronically controlled system. (Savastano et al. 2020)

The difference between a traditional electricity network and a smart grid is shown in Figure 6. The traditional electricity network shows that it produces energy for consumers (red). The smart grid, on the other hand, generates energy for consumers and some consumers (prosumers) also generate energy for the energy market (green).

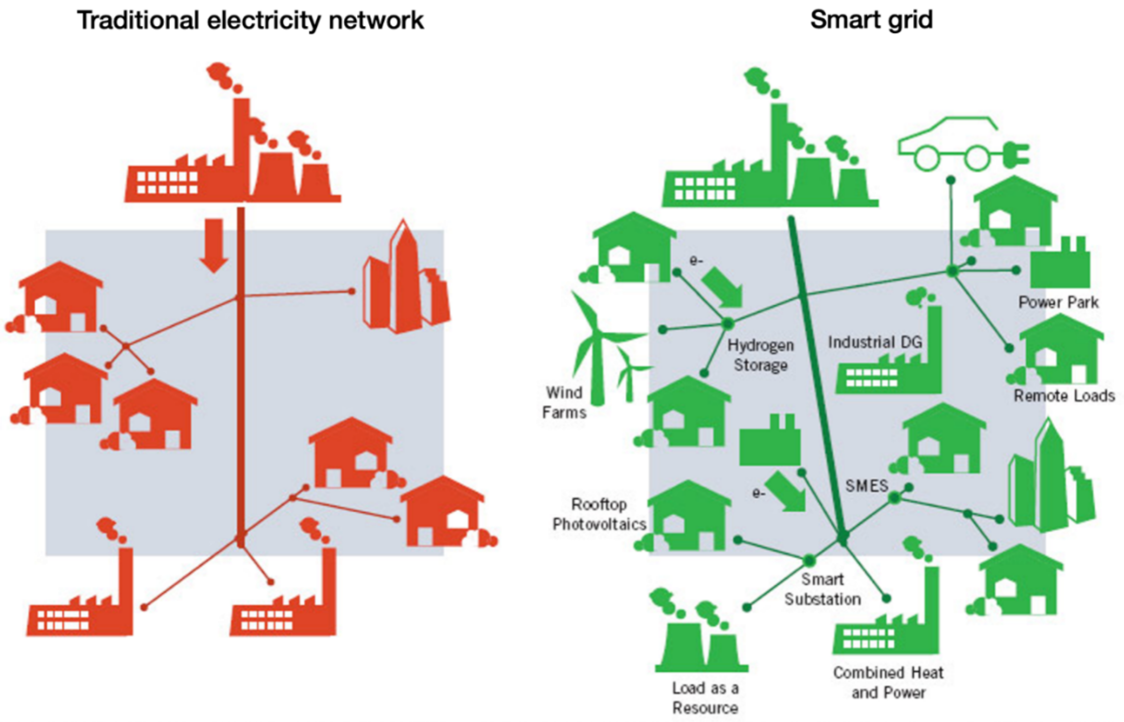

Figure 6. Traditional electricity network and smart grid (under CC BY 3.0 license from Zaremba 2017).

The smart grid has many advantages over a traditional electricity network. For example, when a mid-voltage transformer fails in a distribution network, the smart grid automatically changes the energy flow and restores power supply (Fang et al. 2011). The smart grid can also solve several other problems, such as power cuts and excessive energy consumption, while connecting smart energy control devices to smartphone apps simplifies the monitoring of consumers' energy habits (Savastano et al. 2020).

Smart grids consist of millions of parts, different controls, computers, power lines and new technological devices. In smart cities, the introduction of integrated smart grid systems will result in significant changes to municipal electricity distribution systems and thus affect consumer and producer behaviour. (Savastano et al. 2020)

The smart city is a recent concept whose popularity is growing and coming onto the agenda of researchers and city authorities all over the world (Cameron & Alba 2019). It refers to a well-defined geographical area with high technologies such as ICT, logistics and energy production that work together to create benefits for citizens in terms of well-being, environmental quality and smart development. (Dameri 2013)

Likewise, the smart city can intelligently respond to various needs, such as daily livelihoods, environmental protection, public safety, city services, and industrial and commercial activities. Smart cities can also be said to be the effective integration of smart design ideas, smart building spaces, smart management methods and intelligent development methods. (Su et al. 2011)

2.3.2 Sector coupling

As mentioned above, the need for electricity generation is growing. The number of sectors consuming energy raises important questions regarding electricity use. How much power will be needed if electricity becomes the default form of energy source all over the world? What is the most cost-effective and practical way to store and distribute energy around the world? (Appunn 2018)

The German government is committed to using renewable electricity in many processes. According to the German government, the best way to achieve carbon neutrality is to use renewable energy directly or indirectly (for example power-to-x). The term sector coupling describes the interconnection of energy-consuming sectors. Transportation, industry and buildings (heating) all consume energy. The aim of sector coupling (SC) is to increase the efficiency, versatility and reliability of energy systems. (Appunn 2018)

The operating principle of power-to-x is illustrated in Figure 7. With the interconnection of the energy sectors, some electricity could be used to heat large quantities of water, which could be used, for example, to heat buildings (power-to-heat). During peak hours for electricity generation, electricity could be used to produce hydrogen or synthetic gas (power-to-gas). Stored gas can either be used as a fuel for vehicles (power-to-mobility) or converted back to electricity or heat when solar and wind power production is low. (Appunn 2018)

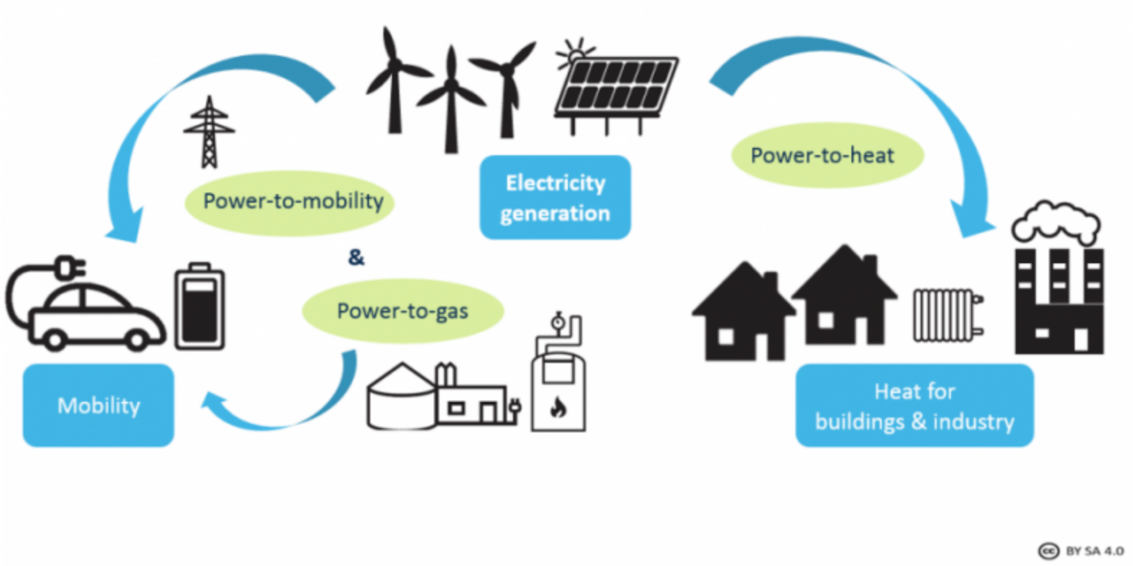

Figure 7. Integrated energy system using renewable electricity (under CC BY-SA 4.0 license from Appunn 2018).

2.3.3 Prosumer

The aim of a smart grid is to provide sustainable energy services, using two-way data and electricity flows, which are enabled by an advanced information, communication and control infrastructure. The most important part of a smart grid is the prosumers. Their role is to generate electricity from renewable sources, use it and distribute it to the smart grid (Savastano et al. 2020; Zafar et al. 2018)

The term prosumer was coined in 1980 by American futurist Alvin Toffler. A prosumer is defined as a consumer who is also involved in the production process. (Dai et al. 2020)

The three functions of the prosumer: consuming, producing and selling energy, are shown in Figure 8. Energy users become consumers when they use local production capacity and producers when they transfer energy produced by solar panels or wind turbines to the local grid. Prosumers are therefore both consumers and producers and in a smart grid, they are also sellers. (Zafar et al. 2018)

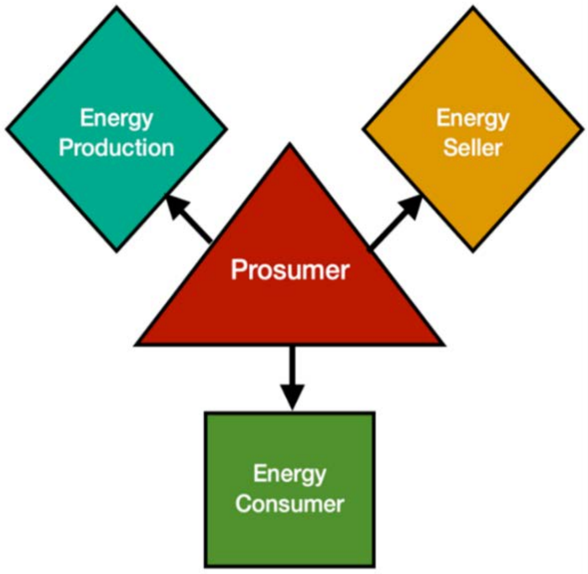

Figure 8. Prosumer concept in simplified form (retelling Zafar et al. 2018).

To meet growing energy needs, smart cities aim to reduce the amount of electricity produced from traditional sources and generate renewable energy instead. Therefore, one part of the smart grid is the installation of solar panels at the consumer's residence, turning them into prosumers. Prosumers are not just private individuals who use electricity produced from their own power supply. Prosumers can also be communities, businesses or public actors such as schools and hospitals. (Savastano et al. 2020)

The prosumer concept is shown in more detail in Figure 9. For example, if prosumers have solar panels on the roof of their house, they use them to generate energy. They can use this energy for example to recharge their electric car. However, at times, solar panels can produce excess energy, allowing the prosumers to sell the surplus energy to the energy market.

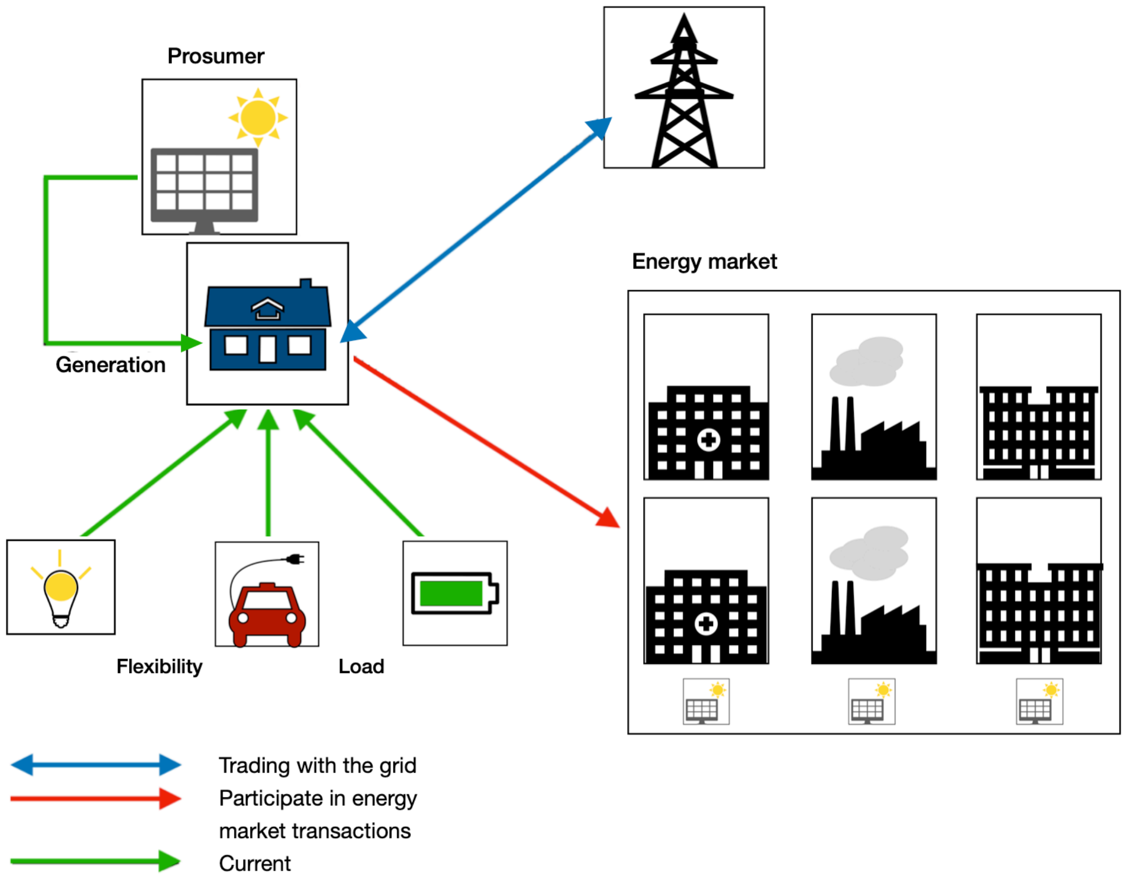

Figure 9. Concept of the prosumer (retelling Dai et al. 2020).

3 MULTI-OBJECTIVE OPTIMIZATION

Optimizing two or more variables at the same time, such as costs and energy efficiency, is called multi-objective optimization (MOO), see for example (Heikkilä 2020). Everyday life is filled with these types of problems, for instance in mathematics, economics, agriculture and the automobile industry (Gunantara 2018).

There are three general approaches to multi-objective optimization: goal attainment, minimax and the Pareto front. The goal attainment approach reduces the values of a linear or nonlinear vector function to reach the target values. Weight vectors are used to express the relative importance of the targets in achieving the objectives. It is possible to face linear and nonlinear limitations when attempting to achieve goals. (MathWorks 2022b)

The minimax approach minimizes the worst values in a set of multivariate functions. There may be linear and nonlinear constraints on these minimizing estimates. (MathWorks 2022b)

The Pareto front approach identifies solutions that require the weakening of one solution in order to improve the other solution. Pareto front solutions can be found using either a direct (pattern) search solver or a genetic algorithm. Both techniques can be applied to smooth or non-smooth problems with linear and nonlinear constraints. (MathWorks 2022b)

The concept of multi-objective optimization was first studied at the end of the 19th century as part of the welfare economy. Researchers Edgeworth and Pareto were the first to introduce MOO. Although there is a long history in the field of multi-objective optimization, economists and mathematicians continue to study it even today. (Lehtonen 2000)

Multi-objective optimization involves more than one objective function that is to be minimized or maximized. Multi-objective analysis is used to define the trade-off among different objectives. The goals of MOO are to find a set of solutions that define the best trade-off between competing objectives. (Purdue University n.d.)

3.1 Optimization techniques

Multi-objective optimization is being studied constantly, leading to the development of specialized algorithms to solve specific problems. Multi-objective optimization problems are solved by using a multi-objective optimization algorithm (MOOA). (Patil & Kulkarni 2020)

In recent years, multi-objective optimization techniques have become more popular. This is because they can be used to solve a wide range of real-life problems, such as those related to bioinformatics, wireless networking, astronomy and astrophysics. (Saini & Saha 2021)

Multi-objective optimization techniques are divided into three main groups: Pareto dominance-based, non-Pareto dominance-based and hybrid MOOA**.** Pareto dominance-based solutions are used when solution x_1 is no worse than solution x_2 in all objectives and solution x_1 is better choice than x_2 in at least one objective, which means that solution x_1 dominates solution x_2. A non-Pareto dominance-based solution gives two objectives where neither of the solutions is better than the other. Both objectives are equally important, for example speed and price. A hybrid MOOA solution is found by combining two or more algorithms from the same or different genres. (Deshpande 2019; Patil & Kulkarni 2020)

Figure 10 shows current multi-objective optimization algorithms. It shows the three major groups of MOOA, and the non-Pareto dominance-based subgroups. Pareto dominance-based and hybrid MOOA also have subgroups, but they are beyond the scope of this study.

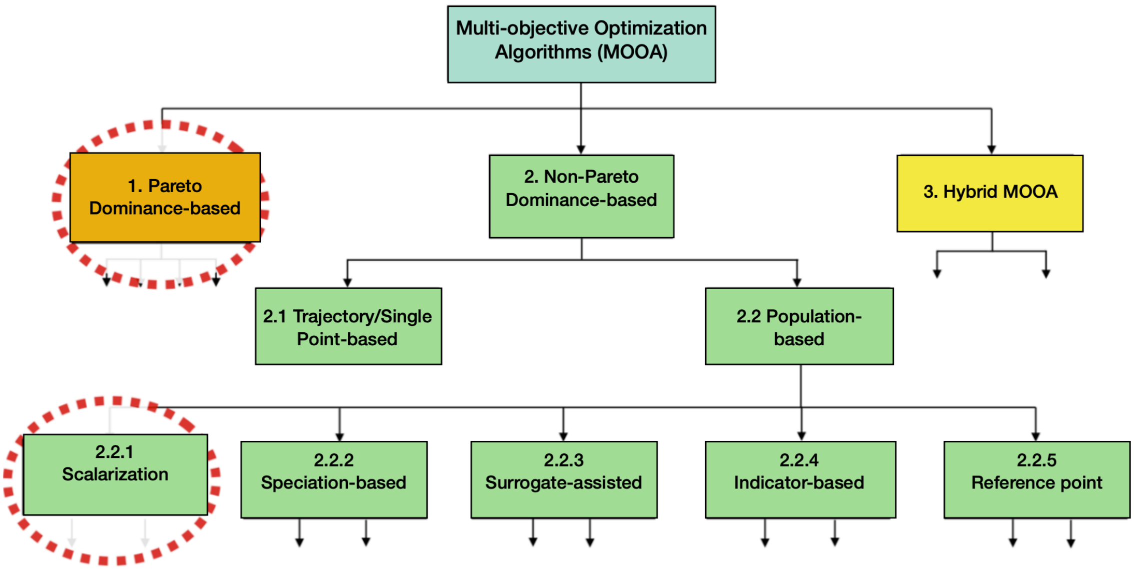

Figure 10. Taxonomy of multi-objective optimization algorithms. The master's thesis is focused on the methods circled in red: Pareto dominance-based and scalarization (retelling Patil & Kulkarni 2020).

In this master's thesis, the Pareto method and scalarization method (subgroup of non-Pareto dominance-based) are presented in more detail. The Pareto and scalarization methods are utilized without the need to formulate complex mathematical equations. By using a constantly updated algorithm, the Pareto method produces an uncontrolled and dominant solution. On the other hand, scalarization produces multi-objective functions that are solved by weights. Three types of weights are used in the scalarization method, namely equal weights, rank order centroid weights (ROC) and rank-sum weights (RS). All three weights are represented by the symbol w_i in the mathematical equation for the scalarization method. (Gunantara 2018)

The Pareto method is dominance-based and scalarization is a non-dominance-based solution. Examples of a non-dominated solution and a dominated solution are shown in Figure 11. In a non-dominated solution, both options x_1 and x_2 are equally good. Option x_1 does not dominate option x_2, nor does option x_2 dominate option x_1. In the dominance-based solution, x_1 is dominated by x_2. In other words, x_1 is a worse option than x_2. (Sela 2020)

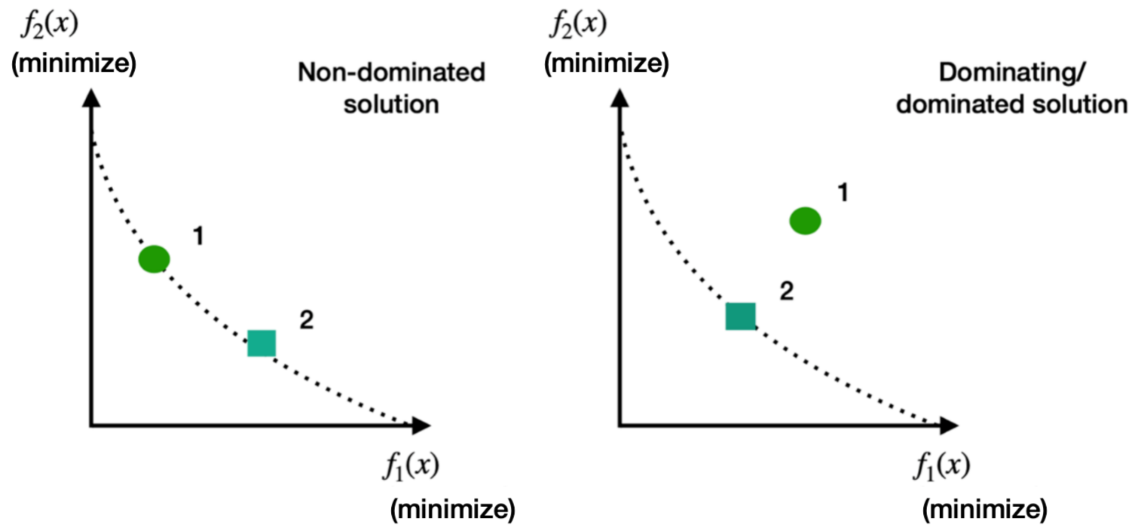

Figure 11. Non-dominated and dominated solutions (retelling Sela 2020).

A multi-objective optimization problem, also known as a vector minimization problem, can be written mathematically as follows (1) (Ehgrott 2005; Goodarzi et al. 2014; Rangaiah 2017):

$$min\ [f_1(X), f_2(X), \ldots, f_k(X)]; \quad X = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}, \tag{1}$$

$$\text{subject to:} \quad \begin{array}{ll} x^L \le x \le x^U & \\ g_i(x) \le 0 & i = 1,2,\ldots,k \\ h_j(x) = 0 & j = 1,2,\ldots,m \end{array}$$

where $f_1(X), f_2(X), \ldots, f_k(X)$ denote the objective functions, x is the decision variable, x^L is the lower bound, x^U is the upper bound, $g_i(x)$ represents the inequality constraint functions and $h_j(x)$ represents the equality constraint functions.

Linear programming (LP) is an optimization problem in which a linear objective function is minimized or maximized according to a linear equality or inequality, depending on various constraints. Linear programming problems are solved by linear expressions called objective functions. They can be used to determine the optimum value, which can be the largest or smallest value depending on the circumstances. The use of LP is common for example in business planning and industrial technology. (Britannica 2022)

3.1.1 Pareto method

Multi-objective optimization generates a set of solutions, known as a Pareto front (PF), which shows the optimal trade-off relationships among all the objectives. The general situation is that there is a conflict between the objectives, with improvements in one causing a decline in another. (Goodarzi et al. 2014, p. 111)

Using the PF method, multi-objective optimization parameters can be limited to effective choices. In this way, compromises can be made rather than studying the entire range of each parameter. (Jahan et al. 2013, p. 64)

The multi-objective optimization problem equation (2) can be written with a Pareto front as follows (Ehrgott 2005):

$$\begin{aligned} f_{1,opt} &= min\, f_1(x) \\ f_{2,opt} &= min\, f_2(x) \\ &\;\;\vdots \\ f_{n,opt} &= min\;\, f_n(x) \end{aligned} \tag{2}$$

where n is the number of objective functions and $f_n(x)$ is the i:th objective function.

With a Pareto front equation, the elements of the solution vectors remain independent throughout optimization and the concept of dominance separates dominated solutions from non-dominated solutions. The optimal value of multi-objective optimization is achieved when one objective function cannot increase further without reducing another. This solution is called Pareto optimality and the set of optimal solutions of MOO are called Pareto optimal solutions. The Pareto front, non-optimal and optimal solutions are shown in Figure 12. The chain of optimal solutions indicated by the red dotted line is called the Pareto front. Non-optimal solutions are those that do not fall on this red dotted line, since they are worse options than those that are on the Pareto front. (Gunantara 2018; Sextos 2018)

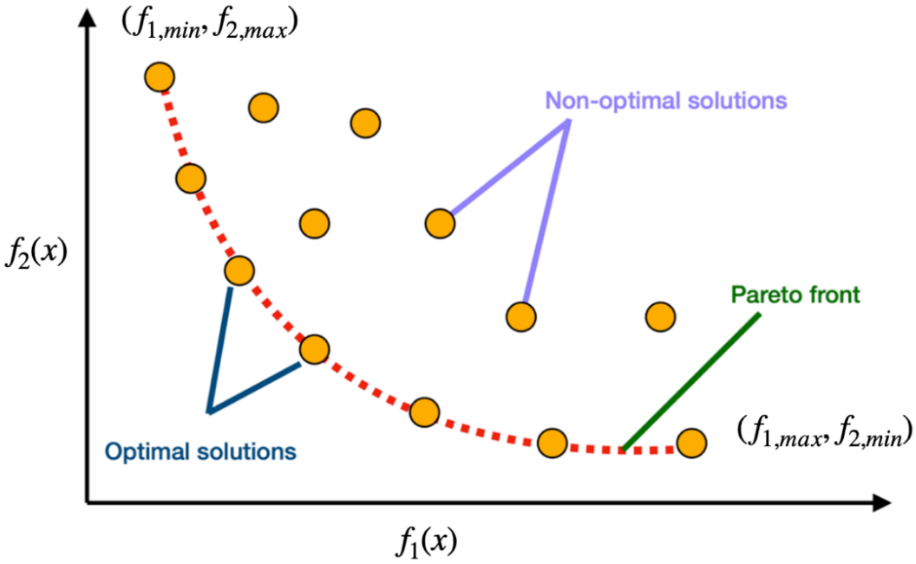

Figure 12. Example of Pareto front, optimal solutions and non-optimal solutions (retelling Sextos 2018).

A set of conditions exists in PF; two of which are the anchor point and the utopia point. An anchor point is obtained by using the best possible objective function. The utopia point (Figure 13) is found by intersecting the maximum and minimum values of the objective function with those of another objective function. (Gunantara 2018)

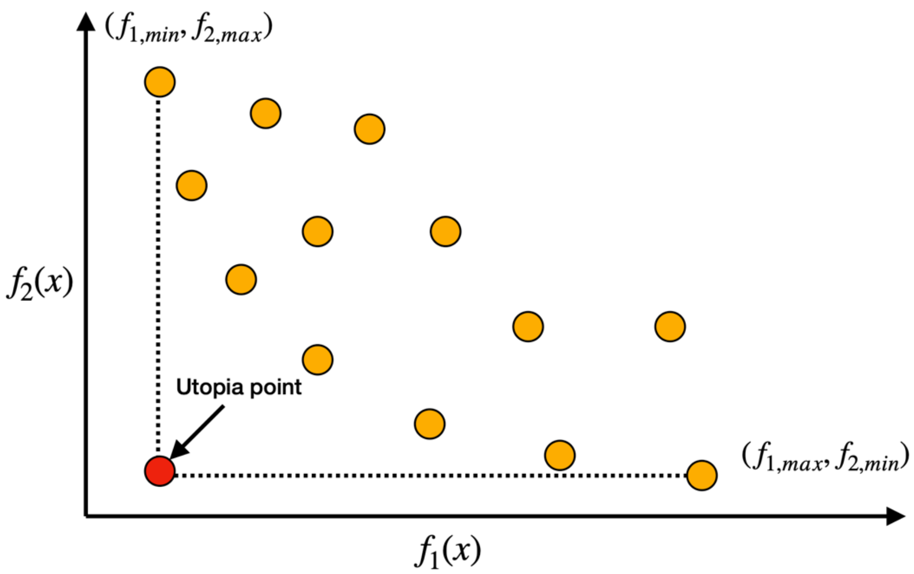

Figure 13. Utopia point (retelling Ameur et al. 2020).

3.1.2 Scalarization method

Multi-objective optimization problems are usually solved using the scalarization method. Scalarization means the replacement of a vector optimization problem with a scalar optimization problem. In other words, the problem is transformed into a family of single objective optimization problems with a real-valued objective function. This is called a scalarization function. Scalarization includes many different techniques that can be used in multi-objective optimization problems, including the weighted sum method and the ε-constraint method. (Ulivieri 2014)

Generally, in the scalarization method, the multi-objective function creates a single solution. The scalarization is calculated using weights that are determined before optimization. A objective function is solved based on the weight of the objective function and the priority of performance. (Gunantara 2018)

As mentioned above, there are three types of weights in the scalarization method: equal weights, rank order centroid weights (ROC) and rank-sum weights (RS). A large weight indicates that a function has a higher priority compared to those with a smaller weight. (Gunantara 2018)

The scalarization method combines multi-objective functions into a scalar objective function as in the following equation (3) (Murata & Ishibuchi 1996, p. 959):

$$f\ (x) = w_1 f_1(x) + w_2 f_2(x) + \ .\ .\ . + w_n f_n(x), \tag{3}$$

where *x* is a solution, *f(x)* is a combined fitness function, $f_i(x)$ is the *i*:th objective function, w_i is a constant weight for $f_i(x)$ and *n* is the number of objective functions.

Equal weights can be determined from the following mathematical equation (4), ROC weights from equation (5) and RS weights from equation (6) (Gunantara 2018):

$$w_i = \frac{1}{n}, \tag{4}$$

$$\mathrm{w_i} = \frac{1}{n} = \sum_{k=1}^{n} \frac{1}{\mathrm{k}}, \tag{5}$$

$$w_i = \frac{2(n+1-i)}{n(n+1)}, \tag{6}$$

where w_i is the weight, i = 1,2,3, …, n and n is the number of objective functions.

The ε-constraint method keeps just one of the objectives, treats the rest as constraints and modifies the constraint value. The ε-constraint methods equation (7) is as follows (Purdue University n.d.):

$$
\begin{aligned}
&\text{Minimize } f_\mu(x), \\
&\text{Subject to: } \quad
\begin{array}{cc}
f_m(x) \le \varepsilon_m, & m = 1,2, \dots, M \ and \ m \ne \mu \\
g_j(x) \ge 0, & j = 1,2, \dots, J \\
h_k(x) = 0, & k = 1,2 \dots, K \\
x_i^{(L)} \le x_i \le x_i^{(U)}, & i = 1,2, \dots n
\end{array}
\end{aligned}
\tag{7}
$$

The advantages and disadvantages of the presented scalarization methods are summarized in Table 1. The weighted sum method is the most famous and widely adopted scalarization method because it is simple and easy to use. (Uliveri 2014; Purdue University n.d.)

Table 1. The advantages and disadvantages of scalarization methods (Purdue University n.d.; Sela 2020).

Method	Advantage	Disadvantage
The weighted sum method	- Simple and easy to use - Guaranteed to find solutions from the entire Pareto-optimal set for convex problems	- Cannot find certain Pareto-optimal solutions in the case of a non-convex objective space. - Difficult to set the weighted vectors to obtain the Pareto-optimal solution in the desired region in objective space. - There is no guarantee that two different sets of weights will lead to two different Pareto-optimal solutions.
The ε-constraint method	- Applicable to either convex or non-convex MOOP - Different Pareto-optimal solutions can be found when using different ε-values.	- The ε-vector must be chosen carefully so that it is within the minimum or maximum values of the individual objective function.

3.2 Objectives and constraints

In multi-objective optimization, there can be several objectives. For example, when designing aircraft with the help of multi-objective optimization, the objectives can be security, maximum speed, landing speed, payload capacity, fuel consumption per hour, comfort and price This shows that many objectives can be pursued simultaneously. In multi-objective optimization the aim is to find the optimal solution that considers all the objectives. In other words, each objective cannot be optimized individually, because the objectives are often conflicting or in competition with each other. (De Vuyst 2020)

In the mathematical formulas of multi-objective optimization, the symbol n reflects the number of objectives. If there is only one objective in a problem, then the solution is handled by optimization techniques. If the problem has two or more objectives, then the solution is handled by multi-objective optimization techniques. (Goodarzi et al. 2014 p. 112)

Multi-objective optimization involves more than one objective. When there are several objectives at the same time, it can lead to a conflict between them. For example, minimizing environmental emissions and minimizing costs are often incompatible objectives. (Sameti & Haghighat 2017)

Therefore, multi-objective optimization usually provides more than one solution. When there are several objectives, typically there may be several optimal solutions. Depending on the situation, the most reasonable option is chosen from these optimal solutions, for example, whether environmental considerations or costs are more important. Figure 14 shows the most commonly used optimization objectives and their conflicts. (Sindhya 2016; Sameti & Haghighat 2017)

Objective functions	Maximum revenue	Minimum production	Minimum emissions	Minimum operation cost	Minimum investment	Minimum fuel cost	Maximum renewables
Maximum revenue	*	D	C	C	D	C	D
Minimum production	D	*	D	C	C	C	D
Minimum emissions	C	D	*	C	C	C	S
Minimum operation cost	C	C	C	*	C	S	C
Minimum investment	D	C	C	C	*	S	C
Minimum fuel cost	C	C	C	S	S	*	C
Maximum renewables	D	D	S	C	C	C	*

Figure 14. Conflict of different objectives. C stands for contrast (in blue), S for supporting (in green) and D for dependent (in yellow), (retelling Sameti & Haghighat 2017).

A multi-objective optimization solution must also consider constraints as well as objectives. In the case of designing aircraft with multi-objective optimization, these constraints include mass, aspect ratio, skin thickness, wing fuel quantity, engine types and fuselage splices (De Vuyst 2020).

It should be noted that the consideration of all possible objectives and constraints in the formulation of the problem gives a comprehensive understanding of the problem. This makes it possible to find the most optimal solution to the situation among all the optimal solutions. (Sindhya 2016)

Whereas multi-objective optimization has multiple objectives and constraints, multi-objective optimization problems usually do not have just one optimal solution. If there are many optimal solutions, how do you know which one is the best? When there are several optimal solutions with different compromises as a solution option, an MOOP decision maker (DM) is needed which selects the most optimal solutions for that specific problem from among all the optimal solutions. If the DM thinks, for example, that some goal should be given more importance, they can request further optimization research. The most optimal solution is not always found after the first optimization. (Sindhya 2016)

3.3 Application in energy systems

Energy is one of the most significant resources in the modern world and it plays a crucial role in sustainable development. Global emissions of greenhouse gases, such as CO_2 emissions, have a major impact on the environment. The most significant source of CO_2 affecting the increase in atmospheric concentration is the burning of fossil fuels. (Sarbu et al. 2019)

Previously, the European Union's goals were to reduce greenhouse gas emissions by 30% and increase the use of renewable energy sources by 20% by 2020. Energy saving is still a topical issue due to high energy demand and greenhouse emissions. District heating systems (DHS) are one of the most practical and sustainable technical solutions that meet consumers' heating needs and reduce greenhouse gas emissions at the same time. Therefore, the European Union's new goals are that, by 2050, 50% of the heating demand should be supplied from DH networks. DH networks can be made even more profitable from the point of view of costs and energy consumption by optimizing planning and operation. (Sarbu et al. 2019)

In the new goals of the European Union, DHC systems are also mentioned. This is because a DHC system can reduce greenhouse emissions and improve energy efficiency by using waste heat and low-temperature renewable energy sources. DHC will play an important role in future energy systems, which is why the definition of an efficient DHC system has been presented in the EU energy directive. (Dorotić et al. 2019)

Dorotić et al. (2019) studied an MOO model for a combined DHC cooling system. In this study, the time frame is a whole year with one-hour time steps. The goal of the research was to minimize the system's total use, discounted investment costs and at the same time minimize the system's CO_2 emissions. To handle the MOO, the DHC system was written in LP format, due to the time scale. In addition to this, the study used a weighted sum method with the ε-constraint method to achieve the Pareto front solution. (Dorotić et al. 2019)

The MOO model of the DHC system developed for this study was defined by two objective functions. These were the minimization of the total costs of the system as well as the minimization of the environmental effects expressed through CO_2 emissions, as shown in equation (8):

$$\min(f_{econ}, f_{ecol}), \tag{8}$$

where f_{econ} is the economic objective function and f_{ecol} is the environmental objective function.

The final MOO solution consisted of points located on the Pareto front. The economic objective function was calculated using equation (9):

$$f_{econ} = \Sigma_i C_{investments,i} + C_{fuel,i} + C_{variable,i} + C_{other,i} - I_{income,i} \tag{9}$$

where $C_{investments,i}$ is the discounted investment cost of the technology, $C_{fuel,i}$ is the technology's fuel costs, $C_{variable,i}$ are the variable costs, $C_{other,i}$ are other costs and $I_{incomei}$ is the additional income from electric energy produced in cogeneration units sold on the electricity market.

Each technology researched in this study had its own investment, fuel and variable costs. In this approach, the investment costs had to be discounted to make it easier to consider the different lifetimes of the technologies used. (Dorotić et al. 2019)

The environmental objective function is presented in equation (10), which was used to calculate the system's total CO_2 emissions (Dorotić et al. 2019):

$$f_{ecol} = \Sigma_{t=1}^{t=8760} \Sigma_i e_{CO_2,i} \times \frac{Q_{i,t}}{\eta_i}, \tag{10}$$

where e_{CO2} is the specific CO_2 emissions for each technology i, $Q_{i,t}$ is defined as the thermal energy production for time step t and technology i, while η_i is the efficiency of technology i.

In the study by Dorotić et al. (2019), two scenarios were developed for the test case of the model. The Croatian city of Velika Gorica was chosen as the target of the case study. The city has several smaller DHSs, although district cooling is not yet available in the city. In scenario 1, the district heating and cooling (DHC) systems work separately and in scenario 2, the DHC systems are combined. From the results of the study, it could be concluded that of these two scenarios, case 2 was more profitable. This was because the combined district heating and district cooling systems operated with the same annual CO_2 emissions as when operating separately, but the total costs were lower. (Dorotić et al. 2019)

In the scientific literature, the optimization of multi-energy systems (MES) is usually based on supply-side management strategies only. Few researchers have studied combined supply and demand side optimization and even in these cases it has only been studied from the perspective of the power grid. (Capone et al. 2021)

In the article by Capone et al. (2021), a case study concerning a complex multi-energy system was analysed. This MES consisted of several end users who already had predetermined heating, cooling and electricity needs. The end users were connected to the local production plant through an infrastructure that included a district heating, cooling and electricity network. The MOO model developed for the case was defined using two objective functions. These included total operating costs and the carbon footprint of the production system. The first step in the study was solely economic optimization and the second step was environmental optimization. There was a large conflict between the two, which led to a multi-objective optimization being performed utilizing the objective function of equation (11):

$$\min_{x \in X}(f_{eco}(x), f_{env}(x)). \tag{11}$$

Based on the results obtained from the MOO, it can be stated that, on the thermal side, greater use of an electric heat pump would increase production costs but help to reduce CO_2 emissions. When the optimization benefits the environmental effects of the production system, the electric heat pump reaches its maximum output at a certain stage, whereupon the CHP is used to satisfy the heat demand. On the cooling side of the system, production takes place either with an electric heat pump, which favours environmental optimization, or with an absorption refrigeration unit, which in turn favours economic optimization. The study obtained the most optimal result with the help of the Pareto front, which gives the solution as a compromise between economic and environmental benefits. The total cost of the optimal solution of this study was 5 560 €/day and the CO_2 emissions were 22.226 kg of CO_2 per day. In this set-up, the heat demand of some end users was shifted, allowing the heat peak to be reduced by up to 37% compared to the non-optimized case. (Capone et al. 2021) In recent years, DHS has been widely studied for possible improvements, from the perspective of fourth- and fifth-generation DHS effects, seasonal thermal energy sustainability and the optimization of CHP plants. A few other multi-objective optimizations of DH systems are listed below. (Sarbu et al. 2019)

Fazlollahi et al. (2015) studied a DH system in their article. They proposed a multi-objective, multi-period model to optimize the design and operation of the DHS. Minimization of the objective functions resulted in maximum efficiency of the DH system and reduced CO_2 emissions as well as other toxic air pollutants (TAC). In their study, the multi-objective problem was solved with mixed-integer-nonlinear programming (MINLP). MINLP is an optimization domain for nonlinear problems involving continuous and integer variables. The results of the study showed that by selecting centralized and decentralized conversion technologies, distribution networks and appropriate resources, environmental impacts could be reduced by 50–65%. In addition to this, the TAC figure could be reduced by 22–27% through the integration of cogeneration technology. (Fazlollahi et al. 2015: Sahinidis 2019)

Li et al. (2016) developed a deterministic multi-objective MILP model. This model optimizes a distributed energy resources (DER) system connected to neighbourhood heating networks containing residential and office buildings. The aim of the study was to minimize the system's CO_2 emissions and TAC emissions. The multi-objective MILP problem of the study was solved using MATLAB® software. In addition to this, the study carried out a sensitivity analysis, which was used to evaluate the effect of different objective function weights on the economic and environmental benefits of the system. (Li et al. 2016)

Morvaj et al. (2016) presented a multi-objective formulation in their article. The formulation of their study was developed to satisfy the demand for thermal and electrical energy in a DH network in an optimal way. This study used the MILP model to minimize total costs and CO_2 emissions. It was solved by the ε-constraint method using IBM ILOG CPLEX, which is a software tool for optimization. (Morvaj et al. 2016; IBM 2022)

Falke et al. (2016) prepared a comprehensive multi-objective optimization model for the design of DHS. In this study, both economic and environmental objectives were considered, and efforts were made to minimize the annual costs of energy supply and CO_2 emissions using an expert advisor (EA). The calculation was simplified by splitting the optimization problem into three sub-problems, and the results obtained were a set of uncontrolled Pareto-efficient solutions. (Falke et al. 2016)

Vesterlund and Toffolo (2017) presented a multi-objective formulation in their article. The formulation presented in this study was a general model developed for modelling and optimizing new and partially extended DH networks. The aim of the model developed in the study was to minimize the investment and operating costs of a DH network. The optimization model in this study was solved using MATLAB® and Simulink® software. (Vesterlund & Toffolo 2017)

In addition to the studies mentioned above, Table 2 also lists the objectives, constraints and software tools of a few other DHS multi-objective optimizations. The main objectives in the above-mentioned research articles are related to economic and environmental issues.

Table 2. Multi-objective optimization methods used in previous studies.

Method/Algorithm	Objectives	Software	Reference
MILP	Both economic and environmental aspects	-	Wu et al. 2016
NLP	- Total exergetic efficiency - Net power	MATLAB®	Sameti et al. 2016
MILP/weighted factor	- Cost - CO_2 emissions	-	Buoro et al. 2013

3.4 Software tools

Many multi-objective optimization software tools have been developed for solving MOO problems. When selecting the software tool, one should consider what are the most important features that it should have. The ideal tool for multi-objective optimization should have an easy-to-use graphical user interface, a wide range of optimization methods, a good tool for visualizing results and selecting the final solutions, as well as durability and reliability of solutions. (Poles et al. 2008)

MATLAB® software includes several tools for multi-objective optimization. For example, its Optimization Toolbox™ provides functionality for finding parameters that minimize or maximize goals and meet constraints. It can be used to solve, for example, linear programming (LP), mixed-integer linear programming (MILP), non-linear programming (NLP) and mixed-integer-nonlinear programming (MINLP) problems. MILP has been adopted as the most widely applicable approach for the optimization of district energy systems. The Optimization Toolbox™ can be used to determine an optimization problem with functions or matrices. (MathWorks 2022c)

The Global Optimization Toolbox can be used to find global solutions to problems that contain several maximum or minimum values. Solvers include pattern search, genetic algorithm and global search. This multi-objective optimization software tool can be used as a solution to optimization problems where the objective or constraint function is continuous, discontinuous, stochastic or contains simulations or black box functions. (MathWorks 2022a)

The MIDACO-Solver is a software tool for numerical optimization problems and is available for several programming languages such as Excel, VBA, Java, MATLAB®, Octave, Python, R and Fortran. It can be applied to continuous (NLP), discrete/integer (IP) and mixed-integer problems (MINLP). MIDACO can be used to solve single optimization problems and multi-objective optimization problems. (MIDACO-Solver 2022)

Kimeme is an optimization software tool designed for multi-objective optimization, which has been developed for the flow of information between professionals and optimization specialists. The Kimeme software tool can be used to design both problems and algorithms. It is integrated with external software such as computer-aided design & engineering (CAD/CAE) packages, MATLAB® and spreadsheets. (Iacca & Mininno 2016)

The ESTECO SpA product, modeFRONTIER, is an integration platform for multi-objective and multi-disciplinary optimization. The modeFRONTIER software tool can be connected to MATLAB® by a MATLAB®node. (ENGINSOFT 2022; MathWorks 2022d)

MOBO is a new software tool for multi-objective building performance optimization. MOBO is a free and commonly used software that can handle single- and multi-objective optimization problems with both continuous and discrete variables. The MOBO software tool can be connected to many external simulation programs. (Palonen et al. 2013)

IDA Indoor Climate and Energy (IDA ICE) is an optimization tool suitable for multi-objective optimization. The software tool accurately models a building, its systems and controllers, ensuring that the lowest possible energy consumption and maximum comfort are achieved. (EQUA 2022)

IOSO is a new generation of non-linear optimization technology. IOSO is suitable for Ansys and SolidWorks users, but is also compatible with MATLAB®, Excel and other modelling tools. (XC Engineering 2022)

Multi-Objective-OPT is a multi-objective optimization tool for non-linear problem solving, suitable for both Excel and MATLAB®. The Multi-Objective-OPT software tool uses the Design of Experiments tool to perform a Pareto analysis. (Multi Global 2022)

The IBM ILOG CPLEX® Optimizer is a software tool that provides flexible and efficient mathematical programming solutions for LP, MILP, quadratic programming and quadratic constrained programming problems (IBM 2022).

4 MATERIALS AND METHODS

The experimental part of the master's thesis focuses on the simulated district heating system of the City of Oulu. The models of the energy system studied include two CHP power stations, eight heat-only boilers (HOB), two heat storage facilities and 10754 buildings. Of these modelled buildings, 2956 are apartment buildings and non-residential buildings where a heat pump can be installed. The purpose of the optimization considered in this study was to maximize profit and minimize emissions. The emission levels studied in the simulation are CO_2 equivalent emissions (CO_2e). The data processing, optimization and simulation work was done using MATLAB® software. An overview of the simulated energy system is shown in Figure 15.

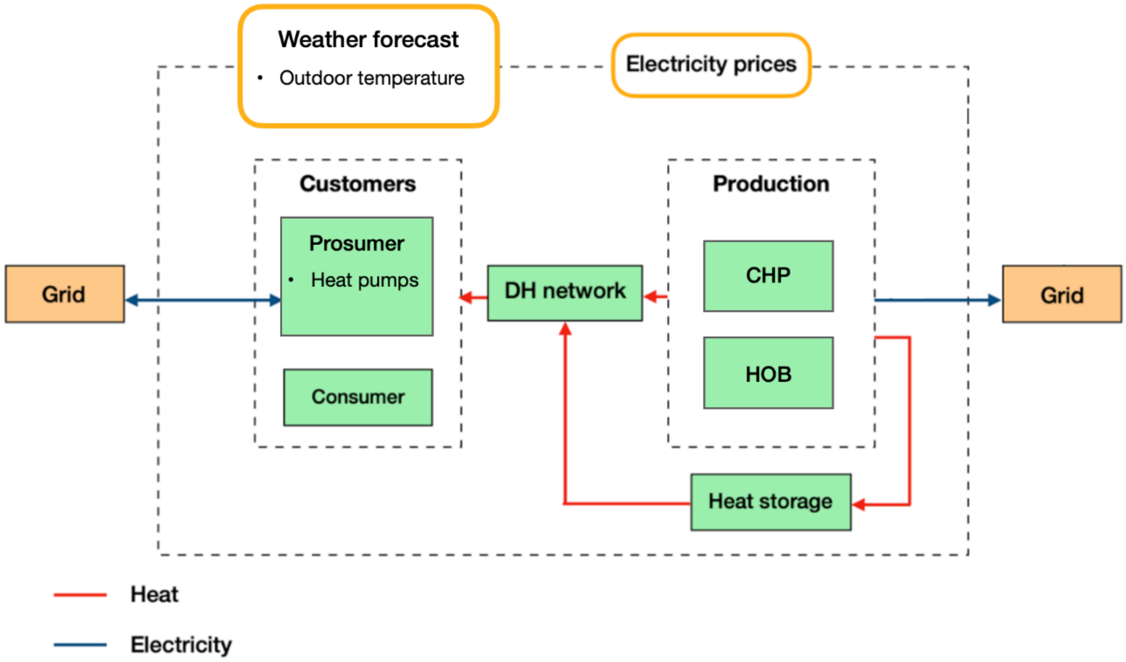

Figure 15. Energy system studied and the variables considered in the simulation.

4.1 Optimization simulator

The optimization simulator utilized in this master's thesis was developed by Dr Petri Hietaharju. It consists of five different steps. In the first step, the measurement data is used to estimate the parameters for heat demand, indoor temperature and heat supply models. In the second step, the demand for heat, heat supply and heat production are predicted. In the third step, the request for flexibility is determined. In the fourth step, the flexibility potential of the buildings is calculated based on the request for flexibility.

In the fifth step, the final multi-objective optimization is performed. Figure 16 illustrates the steps of the optimization simulation. The orange boxes represent the steps of the optimization simulation that were excluded from the scope of this master's thesis. The experimental part of this thesis focuses on step five (the green box in Figure 16) where multi-objective optimization simulation is carried out for the district heat production of the City of Oulu.

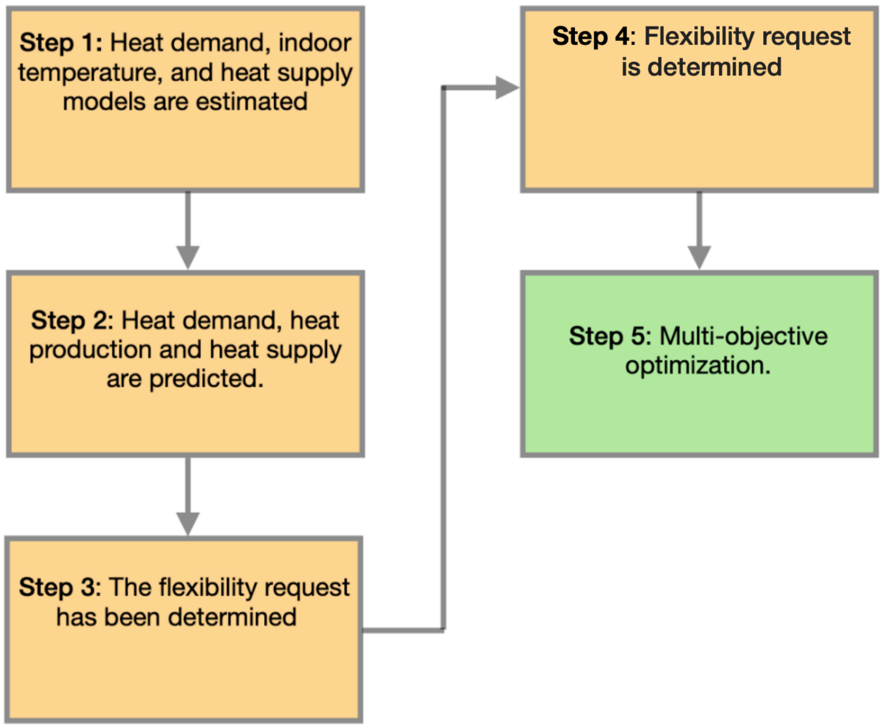

Figure 16. Optimization simulation steps. The green box represents the step performed in the experimental part of this master's thesis.

4.2 Data for optimization

For the experimental part of the master's thesis to be carried out, cost and CO_2e emission data had to be collected. Heat production costs include electricity and fuel costs.

Simulated CHP plants use peat and wood as a fuel. The price of peat used here is 18.0 €/MWh, and its CO_2e emissions are 372.6 kg/MWh. The price of wood is 24.6 €/MWh.

For wood emissions, only methane (CH_4) and nitrous oxide (N_2O) were taken into account, since emissions are reported as equivalent emissions in the thesis. In this case, the emissions of wood are only 3.1 kg/MWh. (Luukko 2019; SYKE 2022)

One of the simulated CHP plants uses 30% peat and 70% wood as fuel, resulting in a fuel cost of 22.6 €/MWh. In this case, the recalculated CO_2e emissions are 30% of the peat's total CO_2e emissions and 70% of the wood's total CO_2e emissions. In this situation, CO_2e emissions are 113.9 kg/MWh. The other CHP plant uses 100% wood as fuel. (Oulun Energia 2022b)

Simulated boilers (HOBs) use light and heavy fuel oil as a fuel. The price of light fuel oil in 2022 was 140.2 €/MWh. The price for heavy fuel oil in 2022 was 84.1 €/MWh. CO_2e emissions from combustion of light fuel oil were 264.2 kg/MWh and from combustion of heavy fuel oil 283.3 kg/MWh. (Hagström 2022; SYKE 2022).

Multi-objective optimization was done using both expensive (high) and affordable (low) electricity prices. The affordable electricity price was taken from the period 5.–8.10.2022 and the expensive electricity price from the period 24.–27.11.2022. Figure 17 shows the high (orange) and low (blue) electricity prices. Emission for purchased electricity were set to 63 kgCO_2e/MWh and include only CO_2 emissions. (Fingrid 2022a)

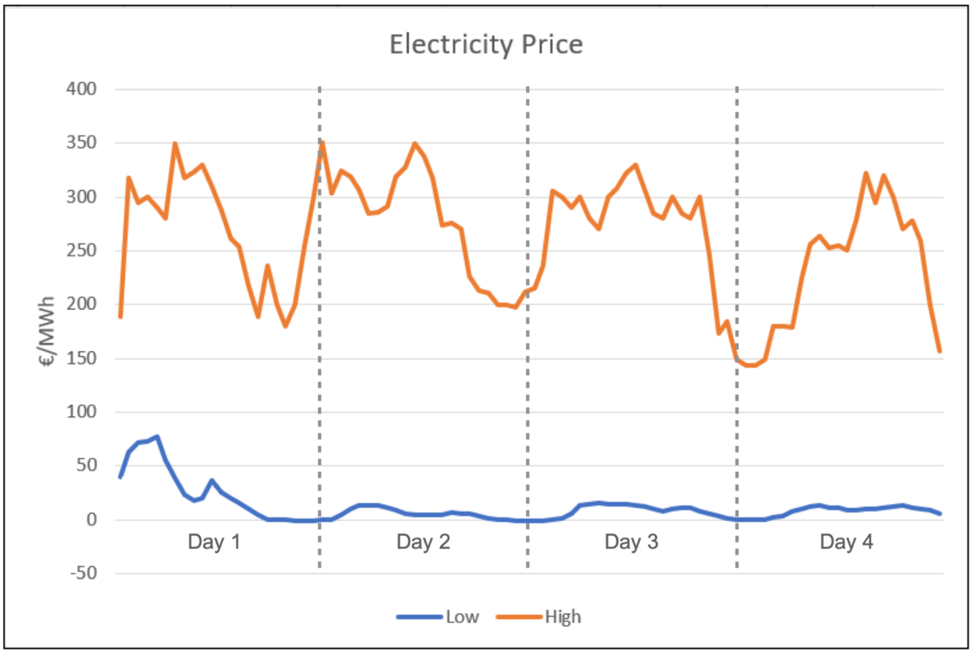

Figure 17. High and low electricity prices for the data to be optimized. The study period is two days, but the data requires four-day electricity prices (retelling Nord Pool 2022).

4.3 Objective function

The aim of the multi-objective optimization in this master's thesis was to maximize profits and minimize emissions. These targets are formulated as two objective functions: economic (f_{econ}) and environmental (f_{env}). The overall objective function is shown in equation (12):

$$J = \min(f_{econ}, f_{env}). \tag{12}$$

The economic objective function is shown in equation (13) and represents profits as it includes both costs and income:

$$f_{econ} = \sum_{t=1}^{48}(C_F(t) + C_{start}(t) + C_{HP}(t) + C_E(t) - I_E(t)), \tag{13}$$

where C_F is the fuel cost [€], C_{start} is the start-up cost of the production plants [€], C_{HP} is the operating cost of the HPs [€], C_E is the cost of bought electricity from the grid [€] and I_E is the income from electricity sold to the grid [€]. Minimizing equation (13) maximizes the profits.

The fuel cost is calculated as shown in equation (14):

$$C_F(t) = \sum_{i=1}^{N_{CHP}}\left(C_{F,CHP,i}F_{CHP,i}(t)\right) + \sum_{i=1}^{N_{HOB}}\left(C_{F,HOB,i}F_{HOB,i}(t)\right), \tag{14}$$

where N_{CHP} is the number of CHP plants, N_{HOB} is the number of HOB plants, $C_{F,CHP,i}$ is the price of fuel for the CHP plant i [€/MWh], $C_{F,HOB,i}$ is the price of fuel for the HOB plant i [€/MWh], $F_{CHP,i}$ is the fuel consumption for the CHP plant i [MWh] and $F_{HOB,i}$ is the fuel consumption for the HOB plant i [MWh].

The start-up costs, operating cost of the HPs, cost of bought electricity and the income from sold electricity are calculated using equations (15)–(18):

$$C_{start}(t) = \sum_{i=1}^{N_{CHP}}\left(C_{start,CHP,i}\delta_{start,CHP,i}(t)\right) + \sum_{i=1}^{N_{HOB}}\left(C_{start,HOB,i}\delta_{start,HOB,i}(t)\right), \tag{15}$$

$$C_{HP}(t) = \sum_{i=1}^{N_{HP}}\left(P_{HP,i}(t)C_{electricity}(t)\right), \tag{16}$$

$$C_E(t) = P_{E,buy}(t)C_{electricity}(t), \tag{17}$$

$$I_E(t) = P_{E,sold}(t)C_{electricity}(t), \tag{18}$$

where $C_{start,CHP,i}$ and $C_{start,HOB,i}$ are the start-up costs for CHP and HOB plants i [€], respectively, $\delta_{start,CHP,I}$ and $\delta_{start,HOB,I}$ are binary variables (which are given a value of one if the plant is started at time t, otherwise their value is zero), N_{HP} is the number of heat pumps, P_{HP} is the electricity consumption of the heat pump [MWh], $C_{electricity}$ is the electricity price [€/MWh], $P_{E,buy}$ is the electricity purchased from the grid [MWh] and $P_{E,sold}$ is the electricity sold to the grid [MWh].

The environmental objective function is shown in equation (19):

$$f_{env} = \Sigma_{t=1}^{48} \sum_{i=1}^{N_{CHP}} \left(e_{CHP,i} F_{CHP,i}(t) \right) + \sum_{i=1}^{N_{HOB}} \left(e_{HOB,i} F_{HOB,i}(t) \right) + \left(e_{grid} P_{E,buy}(t) \right), \tag{19}$$

where $e_{CHP,i}$ is the emissions for the CHP plant i [kgCO$_2$e/MWh], $e_{HOB,i}$ is the emissions for the HOB plant i [kgCO$_2$e/MWh] and e_{grid} is the emissions for the electricity purchased from the grid [kgCO$_2$e/MWh].

4.4 Multi-objective optimization

The multi-objective optimization problem is solved here by applying MILP. Multi-objective optimization in this master's thesis considers the costs and emissions of CHP, HOB and HP according to equations (13)–(19).

The scalarization method is used in this work to solve the multi-objective optimization problem. To be able to do so, the variables in the objective functions must be normalized. This is important as emissions and costs differ from one another. Normalization is done here using equation (20):

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}, \tag{20}$$

where X' is the normalized value of a variable, X is the original value, X_{min} is the minimum value and X_{max} is the maximum value. It is assumed that X_{min} is zero, namely in the minimum situation without energy production. X_{max} is either the maximum costs or the maximum emissions.

Concerning normalization, the overall objective function presented in equation (12) is modified as presented in equation (21):

$$J = min\ (w_1 \frac{f_{econ}}{f_{econ,max}} + w_2 \frac{f_{env}}{f_{env,max}}), \tag{21}$$

where w_1 is the weight for the economic objective function, w_2 is the weight of the environmental objective function, $f_{econ,max}$ is the maximum of the economic objective function and $f_{env,max}$ is the maximum of the environmental objective function.

where w_1 is the weight for the economic objective function, w_2 is the weight of the environmental objective function, $f_{econ,max}$ is the maximum of the economic objective function and $f_{env,max}$ is the maximum of the environmental objective function.

The sum of the weight values w_1 and w_2 must be one, which represents 100%. For example, the weight values of $w_1 = 0.7$ and $w_2 = 0.3$ represent here 70% costs and 30% emissions.

The maximum of the economic objective function can be calculated by equation (22) and the maximum of the environmental objective function can be calculated by equation (23):

$$f_{econ,max} = \sum_{t=1}^{48}\left(C_{F,max}(t) + C_{HP,max}(t) - I_{E,max}(t)\right), \tag{22}$$

$$f_{env,max} = \sum_{t=1}^{48}\left(\sum_{i=1}^{N_{CHP}} e_{CHP,i}F_{CHP,i,max}(t) + \sum_{i=1}^{N_{HOB}} e_{HOB,i}F_{HOB,i,max}(t)\right), \tag{23}$$

where $C_{F,max}$ is the maximum fuel cost calculated with equation (14) using the maximum fuel consumption of the production plant [€], $C_{HP,max}$ is the maximum production cost for HPs calculated by equation (16) using the maximum heat production of the HPs [€], $I_{E,max}$ is the maximum income calculated by equation (18) using the maximum fuel consumption of the CHP plants [€], $F_{CHP,i,max}$ is the maximum fuel consumption of the CHP plant i [MWh] and $F_{HOB,i,max}$ is the maximum fuel consumption of the HOB plant i [MWh] during the following 48 hours.

The optimization was done here using the receding horizon control (RHC) method, also known as model predictive control (MPC). RHC is a control method that involves repeatedly solving a limited optimization problem when using forecasts of future costs, constraints and disruptions on a moving time horizon. (Mattingley 2011)

High and low electricity prices were collected for a four-day period (96 hours). However, the multi-objective optimization period in this study was two days (48 hours). The reason why the data includes electricity prices for 96 hours instead of 48 hours is because the first hour to be optimized uses future electricity price data between hours 1 and 48, the second hour to optimize uses hours from 2 to 49, and the third hour to optimize uses hours from 3 to 50. This process continues until 48 optimized hours have been achieved.

5 RESULTS

In this master's thesis, simulated multi-objective optimization was performed several times to find out the effect of different variables and optimization weights on the results. The investigated variables were weight parameters, the number of heat pumps in the buildings, and the electricity prices at the given period.

Table 3 shows all the multi-objective optimization simulations performed in this study. For 0, 200, 500 and 800 HPs, 15 simulations were made with the high electricity prices and 15 with the low electricity prices. Each of these simulations were repeated three times for 200, 500 and 800 HPs.

Table 3. Scenarios for the multi-objective optimization simulations. In total, eight scenarios were studied. For scenarios 1 and 2, 15 different simulations were done. A total of 45 simulations were done for scenarios 3–8, as each simulation was repeated three times.

Scenario	Number of heat pumps	Electricity price	Number of optimization simulations
1	0	High	15
2	0	Low	15
3	200	High	45
4	200	Low	45
5	500	High	45
6	500	Low	45
7	800	High	45
8	800	Low	45
Total number of optimizations:			300

In each scenario, multi-objective optimization was performed with different weight values for the weights w_1 and w_2. The value of w_1 was decreased by 0.1 from one to zero while w_2 was increased by 0.1 from zero to one. In addition to these 11 simulations (Table 4), four additional simulations with different weight values were also performed for each scenario.

Table 4. Weights w_1 and w_2 in multi-objective optimization simulations with high and low electricity prices. Letter a represents high electricity prices and letter b represent low electricity prices.

Simulation	w_1	w_2
1a,b	1	0
2a,b	0.9	0.1
3a,b	0.8	0.2
4a,b	0.7	0.3
5a,b	0.6	0.4
6a,b	0.5	0.5
7a,b	0.4	0.6
8a,b	0.3	0.7
9a,b	0.2	0.8
10a,b	0.1	0.9
11a,b	0	1

5.1 Optimal weight values for maximizing profits and minimizing emissions

Figure 18 shows the optimized profits and emissions with different w_1 and w_2 values for scenario 1 (simulations 1a–11a, Table 4). The lines for profit and emissions intersect between 0.1/0.9 and 0/1. Therefore, four additional simulations were done with w_1 and w_2 values between those values. In this case, the values studied were 0.08, 0.06, 0.04 and 0.02 for w_1, and 0.92, 0.94, 0.96 and 0.98 for w_2. The profit values in Figure 18 are negative. This means that electricity production generates more income than it costs to produce energy.

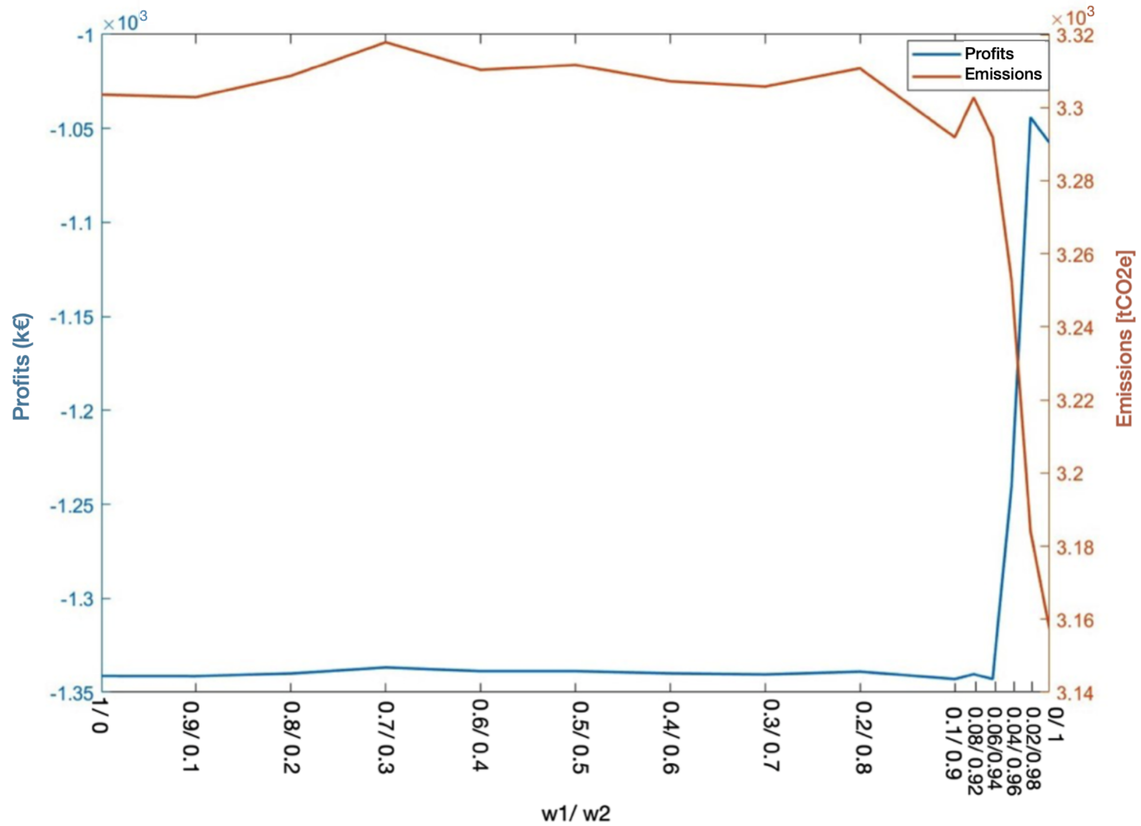

Figure 18. Optimized profits and emissions with different w_1 and w_2 values for scenario 1. The blue line represents profits [k€] and the brown line represents emissions [tCO_2e]. It should be noted that the x- and y-axes of the graphs differ in origin.

Table 5 shows all the optimized profits and emissions with different w_1 and w_2 values for scenario 1, together with the relative change compared with the simulation where only profits are considered (w_1 = 1 and w_2 = 0). It can be noted that weights w_1 = 1–0.06 and w_2 = 0–0.94 in Table 5 show high profits and emissions. However, with weights w_1 = 0.04–0 and w_2 = 0.96–1, profits and emissions decrease.

Table 5. Optimized profits and emissions with different weights w_1 and w_2 for scenario 1. Relative change is calculated in comparison with simulation 1a.

w_1	w_2	Simulation	Profit [k€]	Emissions [tCO_2e]	Relative change [%] profit/emissions
1	0	1a	1341	3304	0.00/0.00
0.9	0.1	2a	1341	3303	0.01/−0.22
0.8	0.2	3a	1340	3309	−0.10/0.15
0.7	0.3	4a	1337	3318	−0.34/0.43
0.6	0.4	5a	1339	3310	−0.19/0.20
0.5	0.5	6a	1339	3312	−0.19/0.25
0.4	0.6	7a	1340	3307	−0.10/0.11
0.3	0.7	8a	1340	3306	−0.001/0.07
0.2	0.8	9a	1339	3311	−0.17/0.22
0.1	0.9	10a	1339	3305	−0.14/0.05
0.08	0.92	12a	1340	3303	−0.07/−0.02
0.06	0.94	13a	1343	3292	0.12/−0.35
0.04	0.96	14a	1240	3253	−7.50/−1.50
0.02	0.98	15a	1044	3184	−22.20/−3.60
0	1	11a	1058	3157	−21.10/−4.43

Figure 19 shows the optimized heat supply in the DH system for scenario 1 with different w_1 and w_2 values. The top figure is the result for the simulation with w_1 = 1 and w_2 = 0, the middle figure is the result for the simulation with w_1 = 0.04 and w_2 =0.96 (intersection of the profit and emission lines in Figure 18), and the bottom figure is the result for the simulation with w_1 = 0 and w_2 = 1.

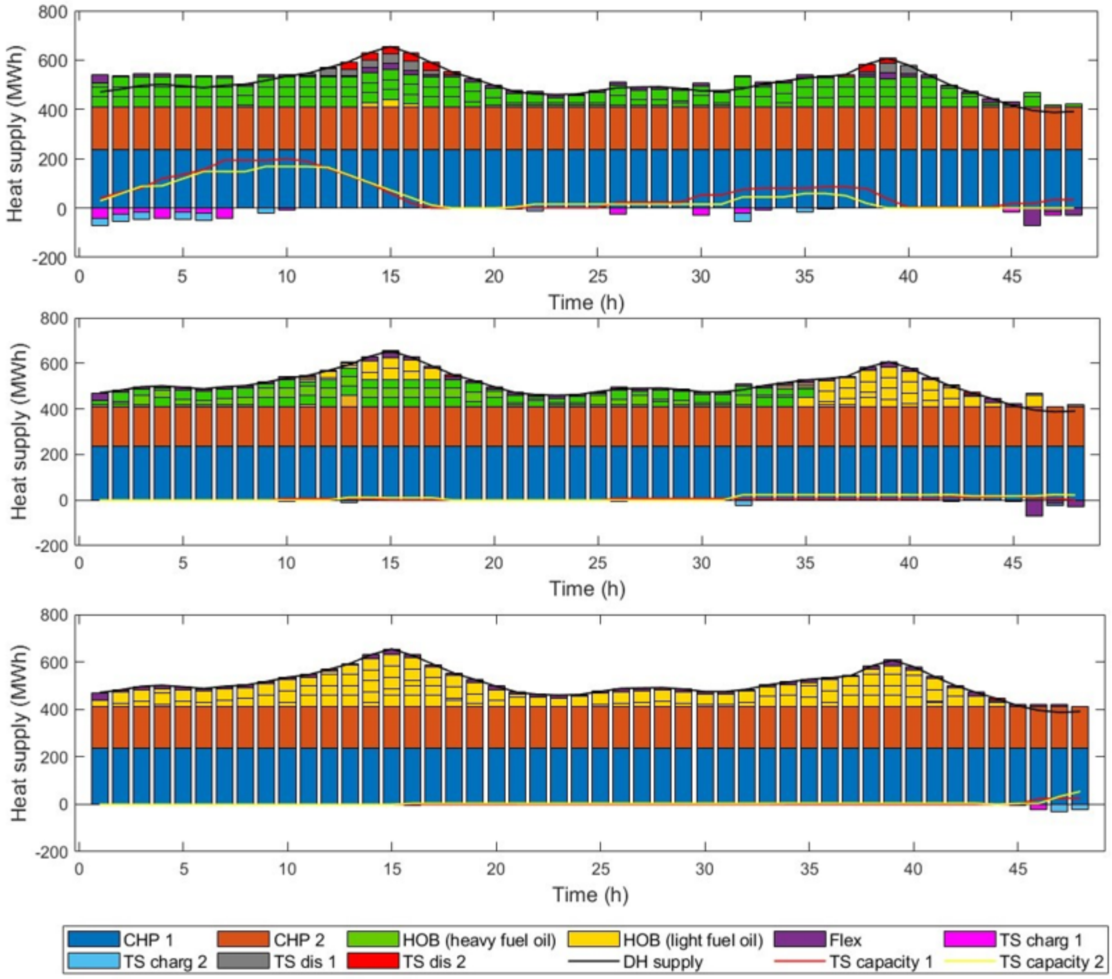

Figure 19. Optimized heat supply for scenario 1. Weight values are $w_1 = 1$ and $w_2 = 0$ (top), $w_1 = 0.04$ and $w_2 = 0.96$ (middle) and $w_1 = 0$ and $w_2 = 1$ (bottom).

Heavy fuel oil is cheaper than light fuel oil. This explains why HOB plants that use heavy fuel oil are utilized when only profits are considered ($w_1 = 1$), as shown in Figure 19 (top). Heat is also stored in this situation. However, the emissions for light fuel oil are lower than those for heavy fuel oil. Therefore, it can be seen from Figure 19 (middle), that in cases where both profits and emissions are considered, HOB plants that use light fuel oil are also utilized. If only emissions are considered ($w_2 = 1$), it can be seen from Figure 19 (bottom) that only HOB plants that use light fuel oil are utilized.

Figure 20 shows the optimized profits and emissions with different w_1 and w_2 values for scenario 2. The lines for profits and emissions intersect between 0.2/0.8 and 0.1/0.9. Therefore, four additional simulations were done with w_1 and w_2 values between those values. In this case, the values studied were 0.18, 0.16, 0.14 and 0.12 for w_1, and 0.82, 0.84, 0.86 and 0.88 for w_2.

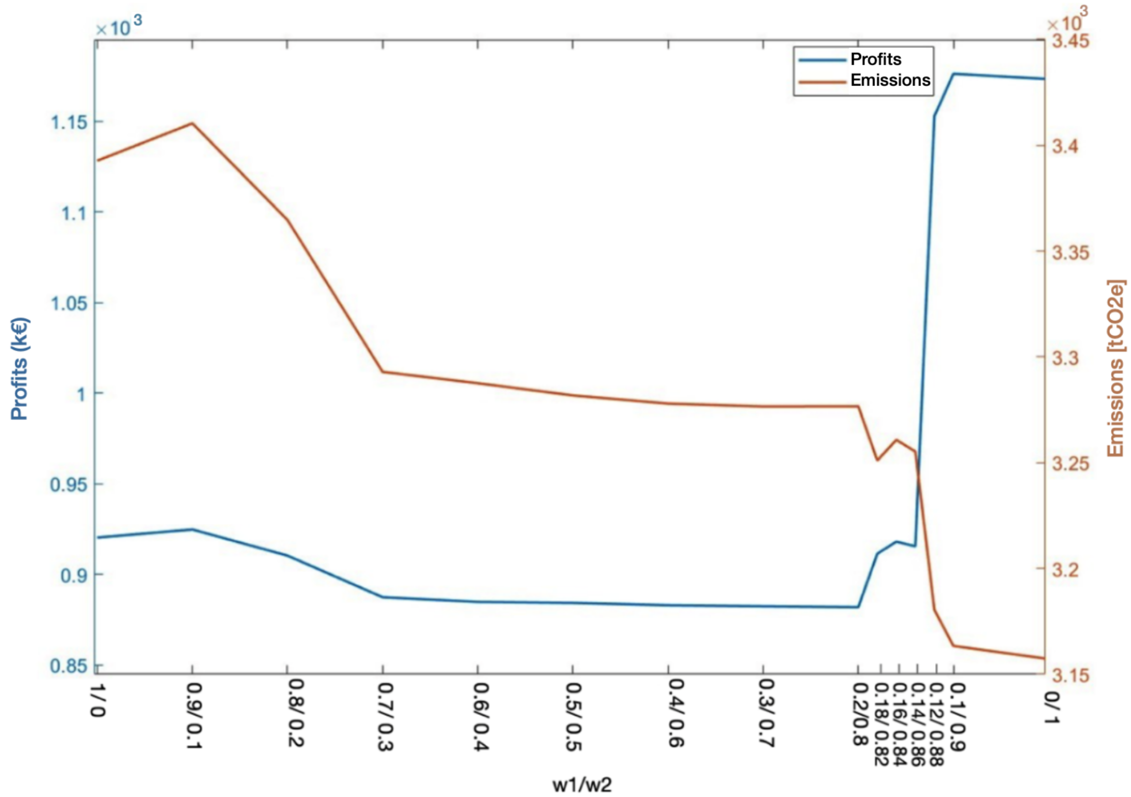

Figure 20. Optimized profits and emissions for scenario 2 with different w_1 and w_2 values. The blue line represents profits [k€] and the brown line represents emissions [tCO_2e].

Table 6 shows all the optimized profits and emissions with different w_1 and w_2 values for scenario 2 together with the relative change compared with the simulation where only profits are considered ($w_1 = 1$ and $w_2 = 0$). The profits are negative in Table 6. This means that more production costs are incurred than income received. It can be noted that the weights w_1 = 1–0.14 and w_2 = 0–0.86 produce more profits and higher emissions. However, with weights w_1 = 0.12–0 and w_2 = 0.88–1, even less profit is produced, but emissions also decrease.

Table 6. Optimized profits and emissions with different weights w_1 and w_2 for scenario 2. Relative change is calculated in comparison with simulation 1b.

w_1	w_2	Simulation	Profit [k€]	Emissions [tCO_2e]	Relative change [%] profits/emissions
1	0	1b	−920	3393	0.00/0.00
0.9	0.1	2b	−925	3410	0.48/0.52
0.8	0.2	3b	−910	3365	−1.10/−0.80
0.7	0.3	4b	−887	3293	−3.60/−2.94
0.6	0.4	5b	−885	3288	−3.85/−3.10
0.5	0.5	6b	−884	3281	−3.90/−3.20
0.4	0.6	7b	−883	3278	−4.05/−3.38
0.3	0.7	8b	−883	3277	−4.10/−3.40
0.2	0.8	9b	−882	3277	−4.17/−3.40
0.18	0.82	16b	−911	3251	−0.97/−4.18
0.16	0.84	17b	−918	3261	−0.24/−3.90
0.14	0.86	18b	−916	3255	−0.50/−4.00
0.12	0.88	19b	−1153	3180	25.20/−6.20
0.1	0.9	10b	−1178	3168	28.04/−6.62
0	1	11b	−1173	3157	27.40/−6.95

Figure 21 shows the optimized heat supply in a DH system for scenario 2 with different w_1 and w_2 values. The top figure is the result for the simulation with $w_1 = 1$ and $w_2 = 0$, the middle figure is the result for the simulation with $w_1 = 0.14$ and $w_2 = 0.86$ (intersection of the profits and emission lines in Figure 20) and the bottom figure is the result for the simulation with $w_1 = 0$ and $w_2 = 1$. Figure 21 shows the same situation as Figure 19. The top figure uses HOB plants which use heavy fuel oil as fuel. The middle figure uses all HOB plants and the bottom one uses HOB plants that use light fuel oil.

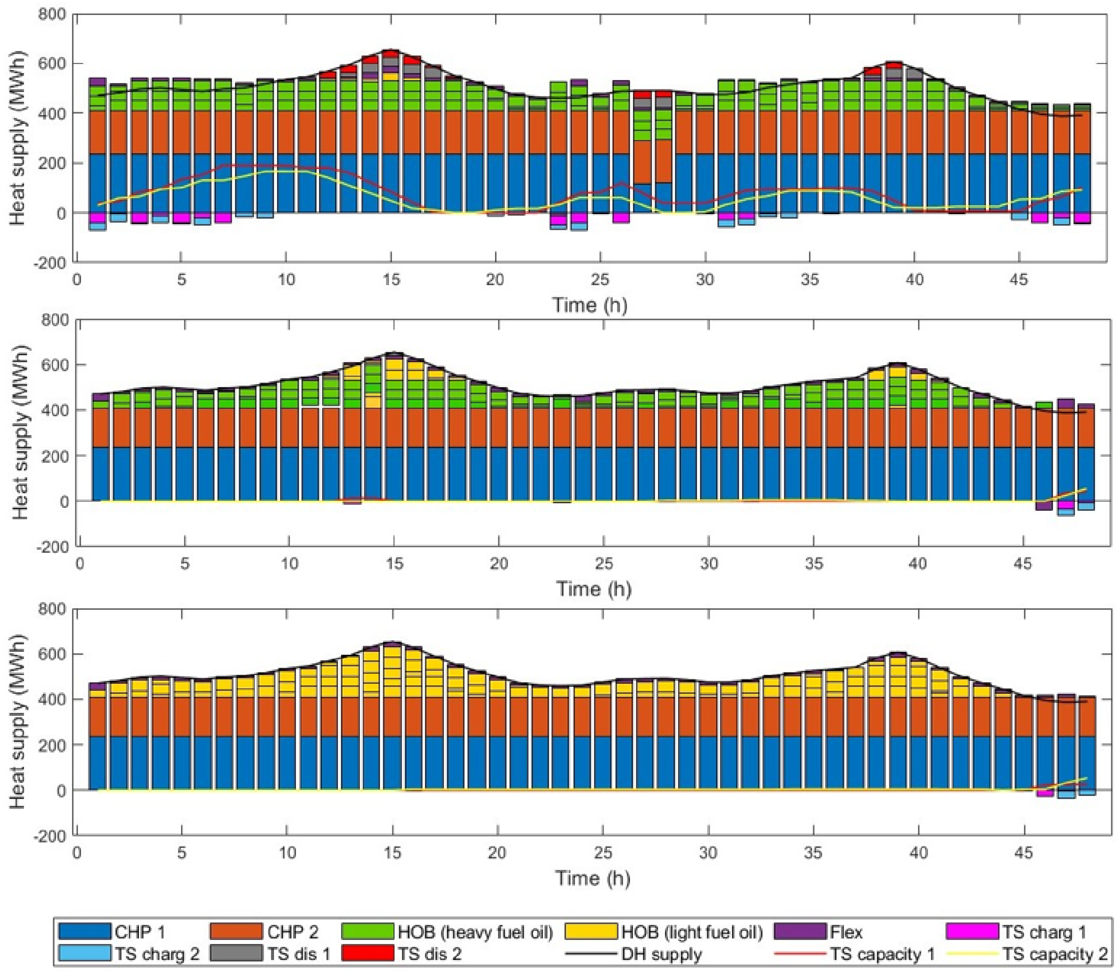

Figure 21. Optimized heat supply for scenario 2. Weight values are $w_1 = 1$ and $w_2 = 0$ (top), $w_1 = 0.14$ and $w_2 = 0.86$ (middle) and $w_1 = 0$ and $w_2 = 1$ (bottom).

5.2 Effect of heat pumps

Next, the effect of HPs on profits and emissions was investigated. In these scenarios, 200, 500 or 800 HPs were added to random apartment and non-residential buildings. It was assumed that the heat pumps were owned by the energy company. Multi-objective optimization with heat pumps was performed with the same weight values as in the cases without heat pumps (see Table 4).

Each optimization was done three times. The weights w_1 and w_2 and the price of electricity are the same at every point. The only difference between the three repetitions is the selection of heat pumps. This selection had to be done before each multi-objective optimization so that the buildings with heat pumps were different. This makes the results more reliable, as more buildings were considered in the multi-objective optimization.

5.2.1 200 heat pumps

Figure 22 shows the optimized profits and emissions for scenario 3 with different weight values. The profit and emission lines intersect between weight values 0.8/0.2 and 0.7/0.3. Therefore, this interval was further investigated by performing four additional simulations with weight values of 0.78, 0.76, 0.74 and 0.72 for w_1 and 0.22, 0.24, 0.26 and 0.28 for w_2.

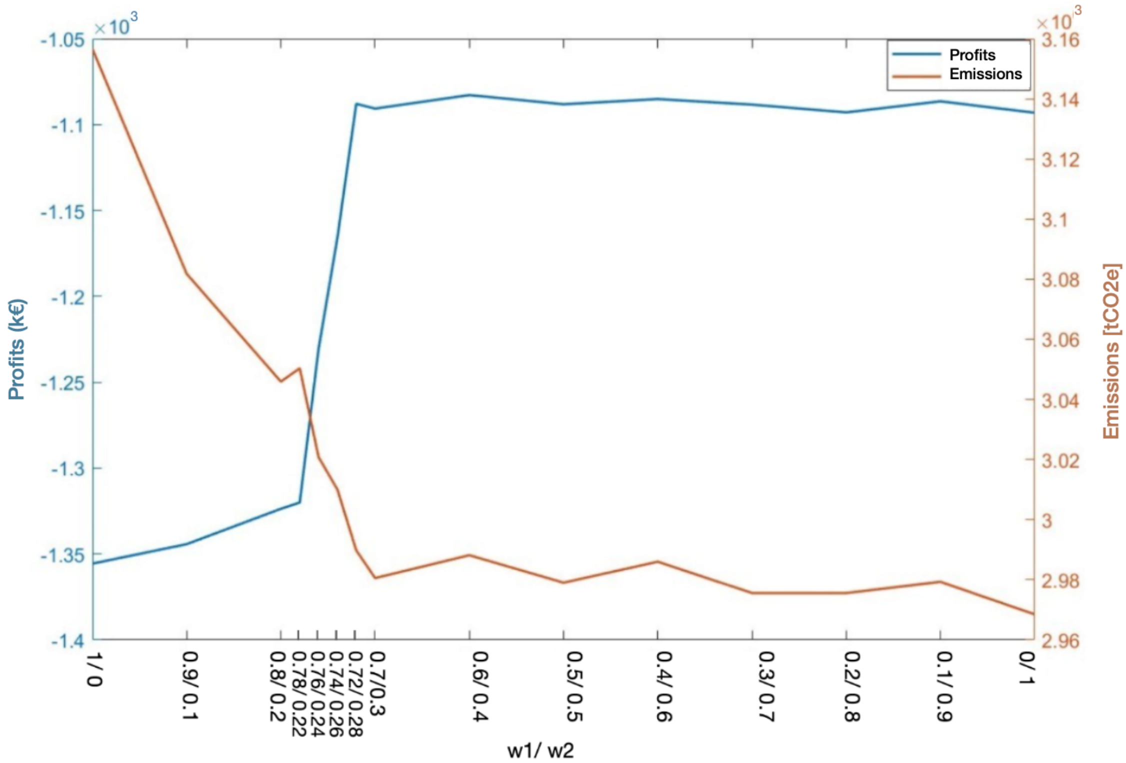

Figure 22. Optimized profits and emissions for scenario 3 with different w_1 and w_2 values. The blue line represents profits [k€] and the brown line represents emissions [tCO_2e].

Table 7 shows all the optimized profits and emissions for scenario 3 with different weight values. The table also shows the standard deviation (Std) of profits and emissions. The relative changes are calculated in comparison with scenario 1 with weights $w_1 = 1$ and $w_2 = 0$. This makes it possible to see the importance of heat pumps in heat production.

Table 7. Average optimized profits and emissions with their standard deviations (Std) for scenario 3 with different w_1 and w_2 values. Relative change is calculated in comparison with scenario 1 with weight values w_1 = 1 and w_2 = 0 (first row).

w_1	w_2	Number of heat pumps	Profit ± Std [k€]	Emissions ± Std [tCO_2e]	Average relative change [%] profits/emissions
1	0	0	1341	3304	0.00/0.00
1	0	200	1354 ± 3.2	3127 ± 37.4	0.94/−5.34
0.9	0.1	200	1345 ± 3.2	3077 ± 29.9	0.26/−6.85
0.8	0.2	200	1316 ± 9.6	3060 ± 16.1	−1.85/−7.39
0.78	0.22	200	1297 ± 42.8	3046 ± 31.6	−3.33/−7.81
0.76	0.24	200	1237 ± 60.2	3030 ± 45.5	−7.80/−8.28
0.74	0.26	200	1175 ± 79.7	3011 ± 45.8	−12.43/−8.84
0.72	0.28	200	1112 ± 40.8	2990 ± 23.6	−17.1/−9.50
0.7	0.3	200	1090 ± 2.3	2980 ± 19.6	−18.72/−9.80
0.6	0.4	200	1084 ± 4.8	2985 ± 21.0	−19.15/−9.65
0.5	0.5	200	1083 ± 4.7	2988 ± 17.1	−19.24/−9.60
0.4	0.6	200	1087 ± 1.9	2980 ± 14.5	−18.96/−9.80
0.3	0.7	200	1086 ± 5.1	2980 ± 21.6	−19.05/−9.80
0.2	0.8	200	1089 ± 5.2	2978 ± 19.1	−18.83/−9.86
0.1	0.9	200	1085 ± 5.7	2981 ± 22.9	−19.10/−9.75
0	1	200	1093 ± 4.3	2967 ± 20.2	−18.49/−10.19

Figure 23 shows the optimized profits and emissions for scenario 4 with different weight values. The profit and emission lines intersect between weight values 0.2/0.8 and 0.1/0.9. Therefore, this interval was further investigated by performing four additional simulations with weight values of 0.18, 0.16, 0.14 and 0.12 for w_1 and 0.82, 0.84, 0.86 and 0.88 for w_2.

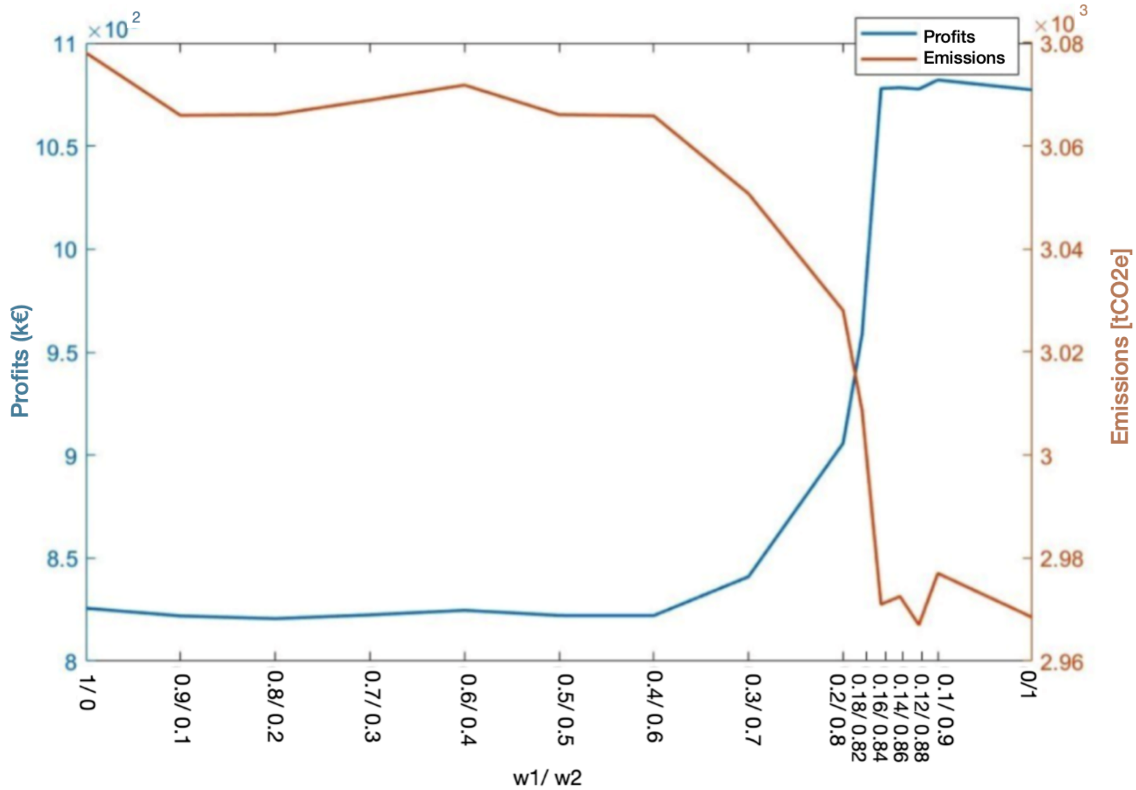

Figure 23. Optimized profits and emissions for scenario 4 with different w_1 and w_2 values. The blue line represents profits [k€], and the brown line represents emissions [tCO_2e].

Table 8 shows all the optimized profits and emissions for scenario 4 with different weight values. It can be seen that 200 heat pumps produce more profits with weights $w_1 = 1-0.2$ and $w_2 = 0-0.8$. This means there are smaller costs to be paid than in the reference situation and emissions are also reduced for each weight value w_1 and w_2.

Table 8. Average optimized profits and emissions with their standard deviations (Std) for scenario 4 with different w_1 and w_2 values. Relative change is calculated in comparison with scenario 1 with weight values w_1 = 1 and w_2 = 0 (first row).

w_1	w_2	Number of heat pumps	Profit ± Std [k€]	Emissions ± Std [tCO_2e]	Average relative change [%] profits/emissions
1	0	0	−920	3393	0.00/0.00
1	0	200	−823 ± 6.2	3070 ± 20.4	10.61/−9.51
0.9	0.1	200	−822 ± 4.1	3069 ± 14.5	10.65/−9.56
0.8	0.2	200	−824 ± 6.6	3072 ± 20.5	10.54/−9.45
0.7	0.3	200	−822 ± 5.3	3068 ± 19.4	10.70/−9.58
0.6	0.4	200	−822 ± 5.9	3067 ± 20.7	10.68/−9.60
0.5	0.5	200	−822 ± 6.6	3065 ± 20.0	10.74/−9.67
0.4	0.6	200	−822 ± 5.5	3068 ± 18.9	10.67/−9.55
0.3	0.7	200	−841 ± 5.8	3051 ± 21.4	8.64/−10.07
0.2	0.8	200	−905 ± 1.1	3026 ± 21.8	1.70/−10.81
0.18	0.82	200	−995 ± 7.8	2998 ± 34.1	−8.11/−11.64
0.16	0.84	200	−1078 ± 11.2	2970 ± 22.2	−17.13/−12.47
0.14	0.86	200	−1078 ± 9.8	2969 ± 19.8	−17.17/−12.48
0.12	0.88	200	−1077 ± 11.3	2968 ± 22.6	−17.04/−12.50
0.1	0.9	200	−1082 ± 8.4	2978 ± 18.0	−17.56/−12.22
0	1	200	−1077 ± 10.2	2967 ± 20.2	−16.98/−12.55

5.2.2 500 heat pumps

Figure 24 shows the optimized profits and emissions for scenario 5 with different weight values. The profit and emission lines intersect between weight values 0/1 and 0.1/0.9. Therefore, four additional simulations were performed with weight values of 0.98, 0.96, 0.94 and 0.92 for w_1 and 0.02, 0.04, 0.06 and 0.08 for w_2.

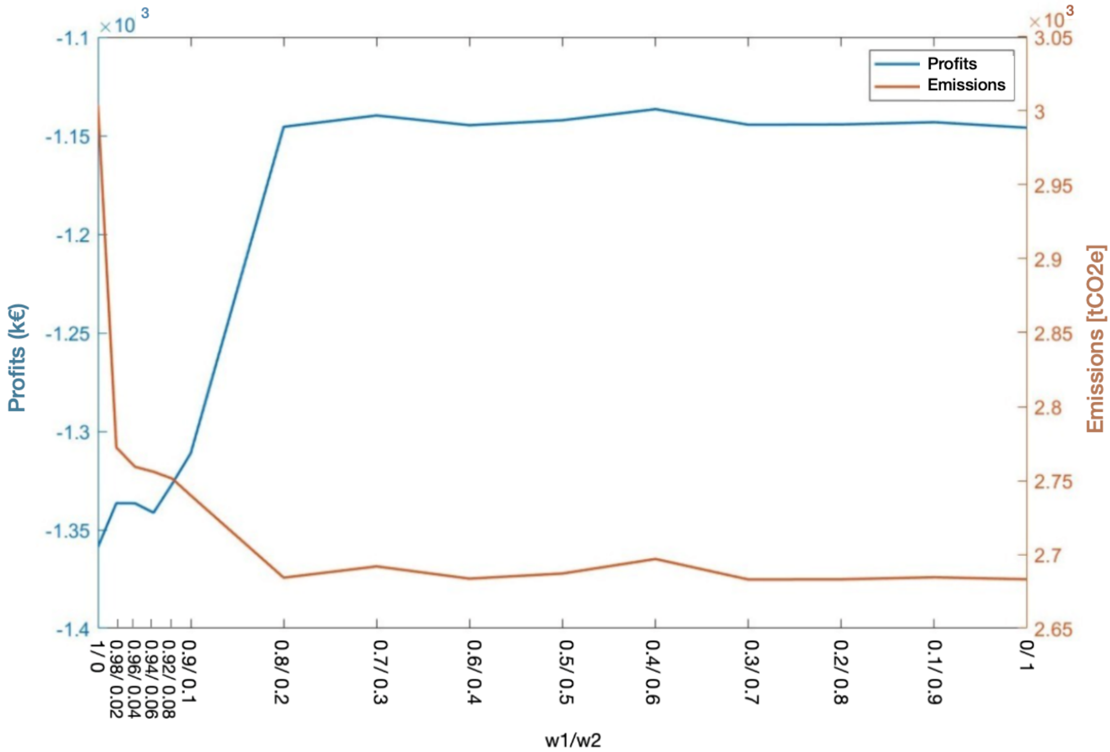

Figure 24. Optimized profits and emissions for scenario 5 with different w_1 and w_2 values. The blue line represents profits [k€] and the brown line represents emissions [tCO_2e].

Table 9 shows all the optimized profits and emissions for scenario 5 with different weight values. Again, the relative changes are calculated in comparison with scenario 1 with weights $w_1 = 1$ and $w_2 = 0$.

Table 9. Average optimized profits and emissions with their standard deviations (Std) for scenario 5 with different w_1 and w_2 values. Relative change is calculated in comparison with scenario 1 with weight values w_1 = 1 and w_2 = 0 (first row).

w_1	w_2	Number of heat pumps	Profit ± Std [k€]	Emissions ± Std [tCO_2e]	Average relative change [%] profits/emissions
1	0	0	1341	3304	0.00/0.00
1	0	500	1358 ± 1.1	3013 ± 9.9	1.28/−8.79
0.98	0.02	500	1377 ± 2.9	2778 ± 12.9	2.68/−15.91
0.96	0.04	500	1338 ± 1.7	2771 ± 10.7	−0.23/−16.11
0.94	0.06	500	1340 ± 0.8	2765 ± 7.5	−0.06/−16.31
0.92	0.08	500	1327 ± 0.7	2757 ± 6.1	−1.06/−16.53
0.9	0.1	500	1316 ± 4.8	2750 ± 8.4	−1.86/−16.77
0.8	0.2	500	1140 ± 7.4	2697 ± 15.6	−14.99/−18.36
0.7	0.3	500	1141 ± 1.8	2694 ± 3.5	−14.94/−18.44
0.6	0.4	500	1141 ± 5.9	2695 ± 12.7	−14.93/−18.41
0.5	0.5	500	1141 ± 1.5	2694 ± 6.1	−14.97/−18.45
0.4	0.6	500	1138 ± 2.4	2698 ± 4.0	−15.12/−18.32
0.3	0.7	500	1142 ± 3.2	2693 ± 9.4	−14.88/−18.49
0.2	0.8	500	1143 ± 1.9	2691 ± 7.3	−14.37/−18.54
0.1	0.9	500	1143 ± 0.7	2690 ± 4.7	−14.77/−18.57
0	1	500	1145 ± 1.5	2689 ± 5.1	−14.67/−18.60

Figure 25 shows the optimized profits and emissions for scenario 6 with different weight values. The profit and emission lines intersect between weight values 0.3/0.7 and 0.2/0.8. Therefore, four additional simulations were performed with weight values of 0.28, 0.26, 0.24 and 0.22 for w_1 and 0.72, 0.74, 0.76 and 0.78 for w_2.

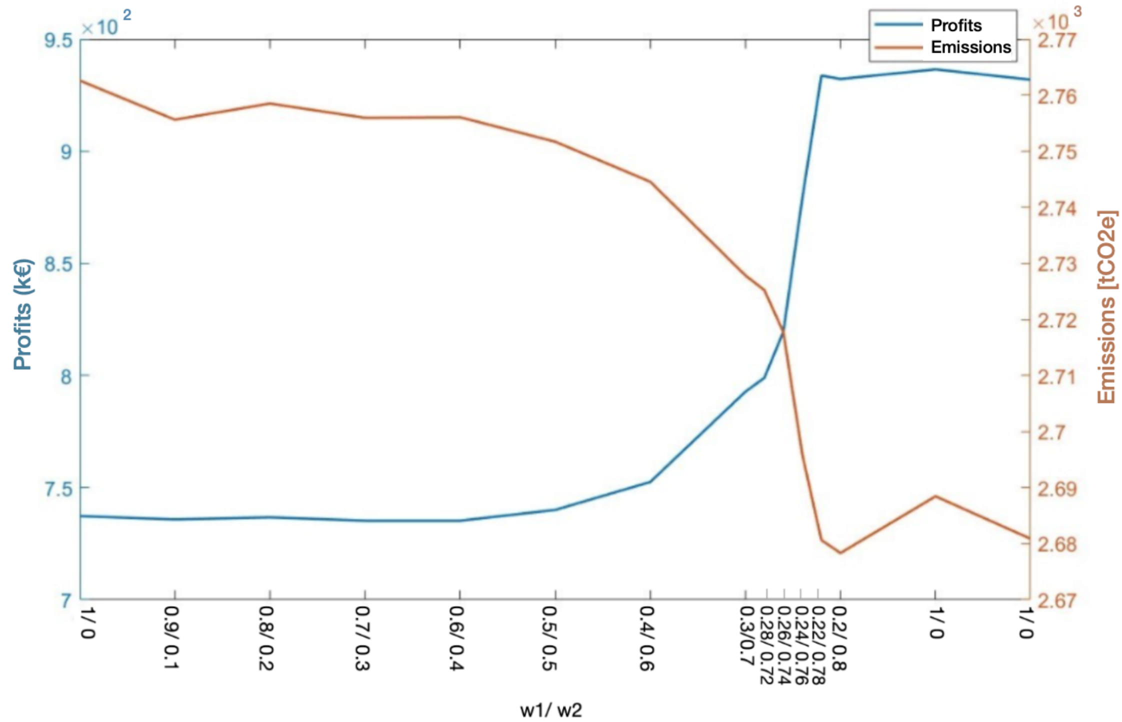

Figure 25. Optimized profits and emissions for scenario 6 with different w_1 and w_2 values. The blue line represents profits [k€] and the brown line represents emissions [tCO_2e].

Table 10 shows all the optimized profits and emissions for scenario 6 with different weight values. It can be seen that 500 heat pumps produce more profits with weights w_1 = 1−0.24 and w_2 = 0−0.76. This means there are smaller costs to be paid than in the reference situation and the emissions have also decreased for each weight value w_1 and w_2.

Table 10. Average optimized profits and emissions for scenario 6 with different w_1 and w_2 values. Relative change is calculated in comparison with scenario 1 with weight values w_1 = 1 and w_2 = 0 (first row).

w_1	w_2	Number of heat pumps	Profit ± Std [k€]	Emissions ± Std [tCO_2e]	Average relative change [%] profits/emissions
1	0	0	−920	3393	0.00/0.00
1	0	500	−738 ± 0.8	2766 ± 3.1	19.78/−18.47
0.9	0.1	500	−738 ± 1.8	2763 ± 6.3	19.83/−18.57
0.8	0.2	500	−739 ± 1.9	2765 ± 6.0	19.72/−18.50
0.7	0.3	500	−738 ± 2.3	2764 ± 6.9	19.82/−18.54
0.6	0.4	500	−737 ± 2.0	2763 ± 6.1	19.87/−18.56
0.5	0.5	500	−742 ± 3.2	2760 ± 7.5	19.33/−18.65
0.4	0.6	500	−752 ± 1.4	2753 ± 7.8	18.30/−18.84
0.3	0.7	500	−796 ± 2.6	2736 ± 7.1	13.53/−19.37
0.28	0.72	500	−804 ± 5.7	2733 ± 7.1	12.67/−19.44
0.26	0.74	500	−820 ± 2.9	2728 ± 8.7	10.91/−19.61
0.24	0.76	500	−871 ± 1.1	2708 ± 11.0	5.39/−20.17
0.22	0.78	500	−937 ± 2.8	2687 ± 5.7	−1.77/−20.81
0.2	0.8	500	−936 ± 3.7	2686 ± 7.1	−1.73/−20.82
0.1	0.9	500	−941 ± 4.9	2697 ± 9.6	−2.19/−20.52
0	1	500	−936 ± 3.4	2688 ± 6.4	−1.67/−20.76

5.2.3 800 heat pumps

Figure 26 shows the optimized profits and emissions for scenario 7 with different weight values. The profit and emission lines intersect between weight values 1/0 and 0.9/0. Therefore, four additional simulations were performed with weight values of 0.98, 0.96, 0.94 and 0.92 for w_1 and 0.02, 0.04, 0.06 and 0.08 for w_2.

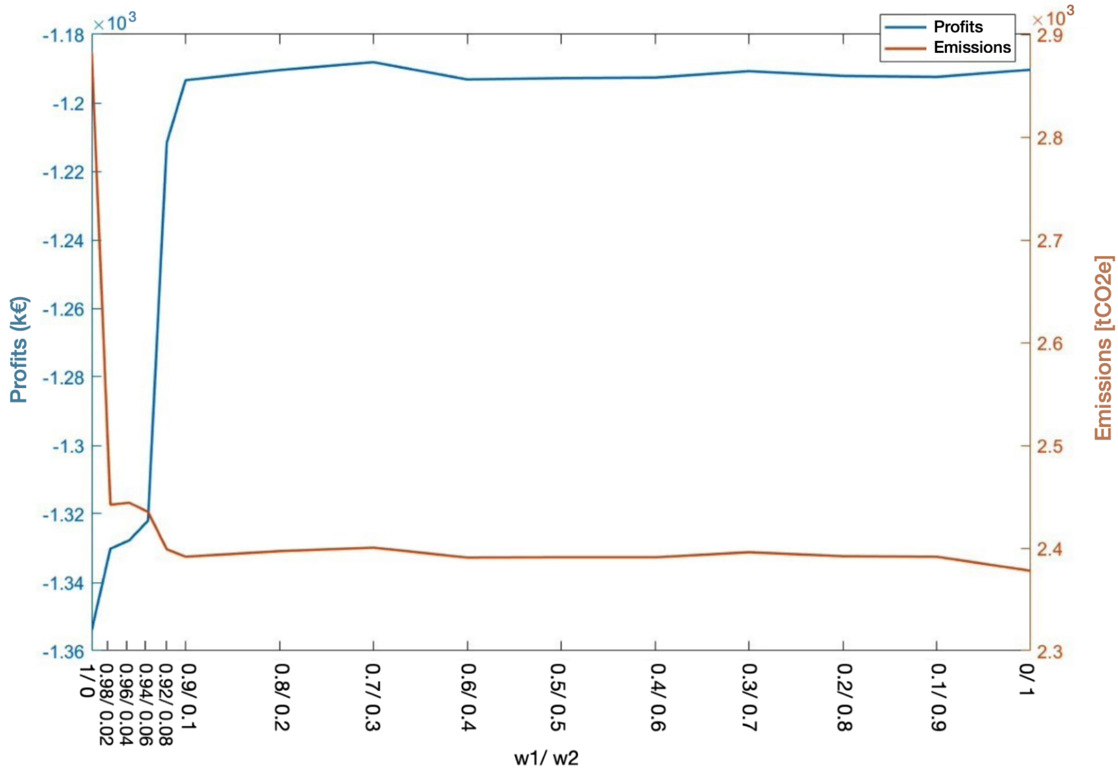

Figure 26. Optimized profits and emissions for scenario 7 with different w_1 and w_2 values. The blue line represents profits [k€] and the brown line represents emissions [tCO_2e].

Table 11 shows all the optimized profits and emissions for scenario 7 with different weight values. Again, the relative changes are calculated in comparison with scenario 1 with weights $w_1 = 1$ and $w_2 = 0$. This makes it possible to see the importance of heat pumps in heat production.

Table 11. Average optimized profits and emissions with their standard deviations (Std) for scenario 7 with different w_1 and w_2 values. Relative change is calculated in comparison with scenario 1 with weight values w_1 = 1 and w_2 = 0 (first row).

w_1	w_2	Number of heat pumps	Profit ± Std [k€]	Emissions ± Std [tCO_2e]	Average relative change [%] profits/emissions
1	0	0	1341	3304	0.00/0.00
1	0	800	1360 ± 4.9	2852 ± 33.2	1.37/−13.66
0.98	0.02	800	1330 ± 1.7	2435 ± 13.3	−0.86/−26.28
0.96	0.04	800	1328 ± 0.5	2431 ± 19.2	−0.98/−26.40
0.94	0.06	800	1320 ± 3.0	2426 ± 16.6	−1.61/−26.57
0.92	0.08	800	1203 ± 8.4	2387 ± 17.4	−10.28/−27.73
0.9	0.1	800	1192 ± 4.4	2386 ± 20.1	−11.10/−27.76
0.8	0.2	800	1193 ± 2.8	2384 ± 18.1	−11.00/−27.82
0.7	0.3	800	1192 ± 3.4	2386 ± 18.2	−11.13/−27.78
0.6	0.4	800	1194 ± 1.9	2382 ± 16.7	−10.96/−27.90
0.5	0.5	800	1194 ± 2.9	2382 ± 18.1	−11.01/−27.89
0.4	0.6	800	1194 ± 2.4	2381 ± 17.2	−10.97/−27.92
0.3	0.7	800	1193 ± 3.0	2384 ± 18.8	−11.05/−27.85
0.2	0.8	800	1193 ± 1.2	2383 ± 15.1	−11.05/−27.86
0.1	0.9	800	1194 ± 2.5	2382 ± 17.5	−10.98/−27.91
0	1	800	1192 ± 2.5	2368 ± 18.3	−11.16/−28.32

Figure 27 shows the optimized profits and emissions for scenario 8 with different weight values. The profit and emission lines intersect between weight values 0.4/0.6 and 0.3/0.7. Therefore, four additional simulations were performed with weight values of 0.38, 0.36, 0.34 and 0.32 for w_1 and 0.62, 0.64, 0.66 and 0.68 for w_2.

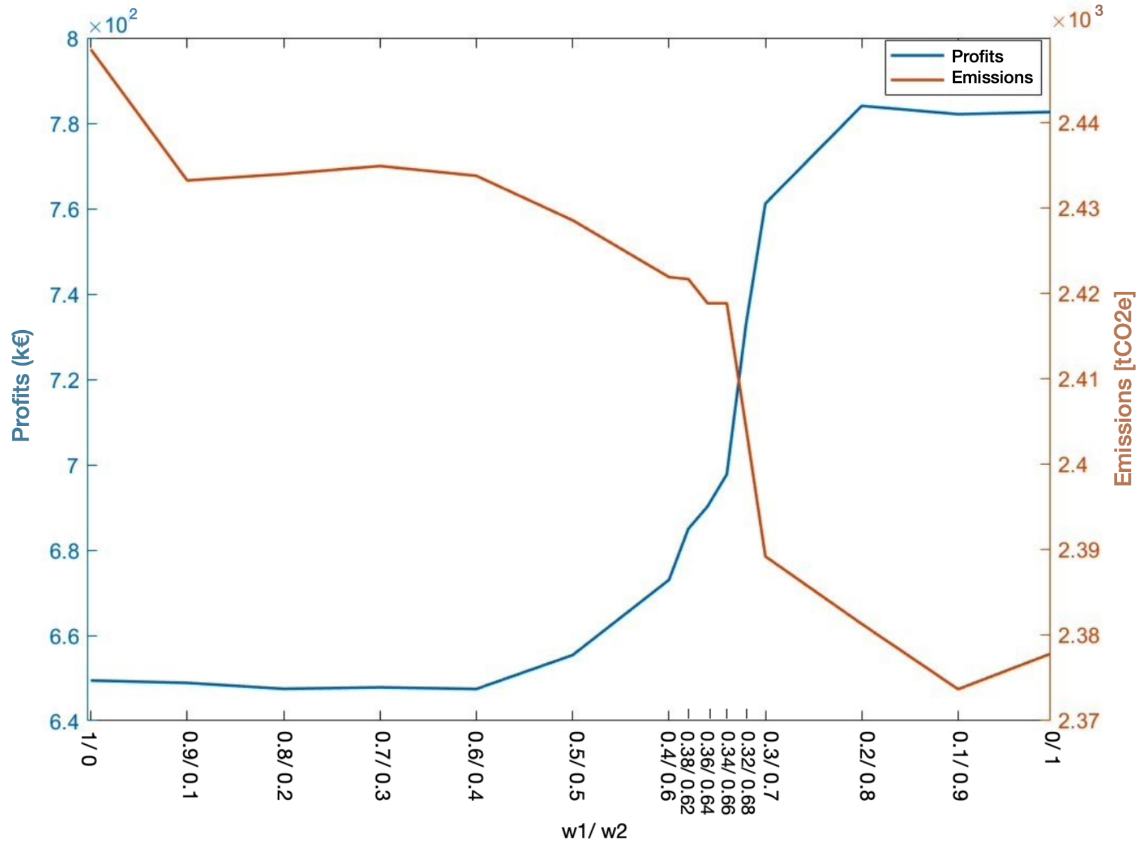

Figure 27. Optimized profits and emissions for scenario 8 with different w_1 and w_2 values. The blue line represents profits [k€] and the brown line represents emissions [tCO_2e].

Table 12 shows all the optimized profits and emissions for scenario 8 with different weight values. It can be seen that 800 heat pumps produce more profits, which means there are smaller costs to be paid than in the reference situation and the emissions have also decreased significantly.

Table 12. Average optimized profits and emissions with their standard deviations (Std) for scenario 8 with different w_1 and w_2 values. Relative change is calculated in comparison with scenario 1 with weight values w_1 = 1 and w_2 = 0 (first row).

w_1	w_2	Number of heat pumps	Profit ± Std [k€]	Emissions ± Std [tCO_2e]	Average relative change [%] profits/emissions
1	0	0	−920	3393	0.00/0.00
1	0	800	−645 ± 5.9	2434 ± 20.7	29.88/−28.25
0.9	0.1	800	−646 ± 5.8	2425± 20.2	29.84/−28.52
0.8	0.2	800	−645 ± 4.4	2424 ± 20.0	29.88/−28.56
0.7	0.3	800	−645 ± 5.2	2424 ± 19.1	29.95/−28.57
0.6	0.4	800	−645 ± 5.1	2426 ± 19.2	29.87/−28.50
0.5	0.5	800	−653 ± 6.9	2418± 18.4	29.03/−28.74
0.4	0.6	800	−672 ± 4.6	2411± 19.1	27.04/−28.94
0.38	0.02	800	−683 ± 3.7	2410 ± 18.0	25.81/−28.96
0.36	0.04	800	−686 ± 6.6	2410 ± 17.7	25.47/−28.98
0.34	0.06	800	−691 ± 10.8	2406 ± 20.0	24.94/−29.10
0.32	0.08	800	−731 ± 5.8	2390 ± 20.1	20.57/−29.56
0.3	0.7	800	−764 ± 4.9	2378 ± 19.2	16.97/−29.91
0.2	0.8	800	−779 ± 8.3	2372 ± 17.1	15.32/−30.01
0.1	0.9	800	−777 ± 8.8	2364 ± 18.4	15.56/−30.35
0	1	800	−778 ± 9.1	2368 ± 18.3	15.48/−30.20

5.3 Overview

Figure 28 shows profits for 200, 500 and 800 HPs with high electricity prices. The blue bars illustrate 200, 500 and 800 HPs with weights w_1 =1 and w_2 = 0 and the green bars illustrate the situation with weights w_1 =0 and w_2 = 1 for 200, 500 and 800 HPs. The situation with w_1 =1 and w_2 = 0, zero heat pumps and high electricity prices is used as a reference point for comparison with other situations. Profits for this situation are € 1 341 295, which means 0% in this case.

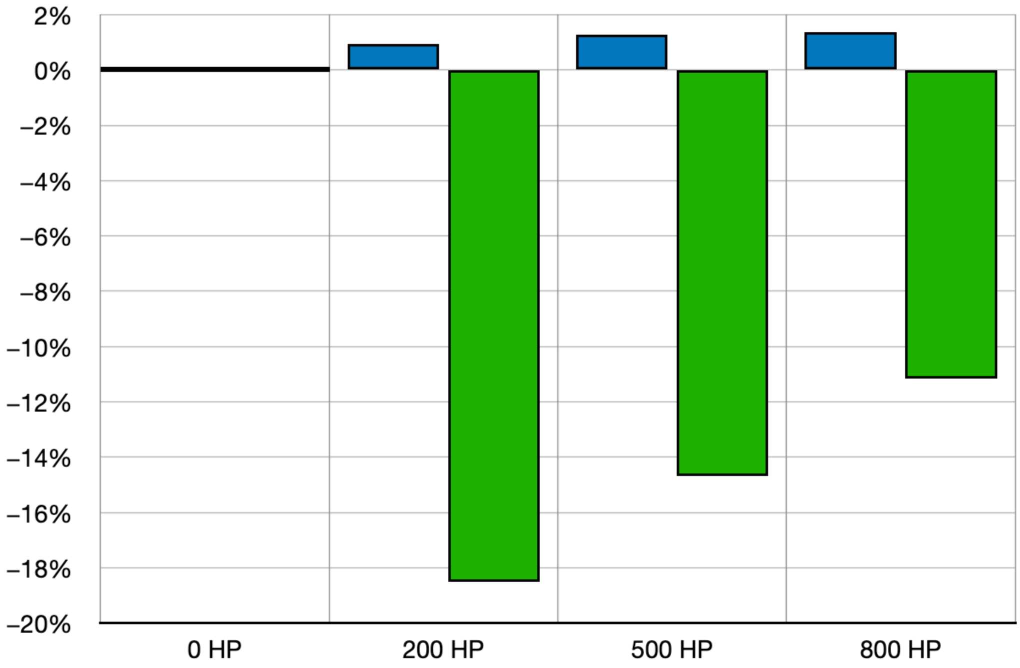

Figure 28. Relative change in profits (%) with high electricity prices and different numbers of heat pumps. Relative change is in comparison with the case without heat pumps. Blue bars represent the results with weight values $w_1 = 1$ and $w_2 = 0$ while green bars represent the results with weight values $w_1 = 0$ and $w_2 = 1$.

Figure 28 shows that during the period of high electricity prices in both situations, $w_1 = 1$ and $w_2 = 0$, as well as $w_1 = 0$ and $w_2 = 1$, when the number of heat pumps increases, so do the profits. For example, the profits with 200 HPs are significantly lower than with 800 HPs in the situation of $w_1 = 0$ and $w_2 = 1$. Also, it is worth noting that in the situation with $w_1 = 1$ and $w_2 = 0$, more profits are generated than in the reference situation. In a situation with $w_1 = 0$ and $w_2 = 1$, less profits are generated than in the reference situation.

Figure 29 shows the emissions of 200, 500 and 800 HPs for the period of high electricity prices. The yellow bars illustrate 200, 500 and 800 HPs with weights $w_1 = 1$ and $w_2 = 0$ and the orange bars illustrate the situation with weights $w_1 = 0$ and $w_2 = 1$ for 200, 500 and 800 HPs. The situation with $w_1 = 1$ and $w_2 = 0$, zero heat pumps and low electricity prices is used as a reference point for comparing other situations. Emissions for this situation are 3 303 542 kg, which means 0% in this case.

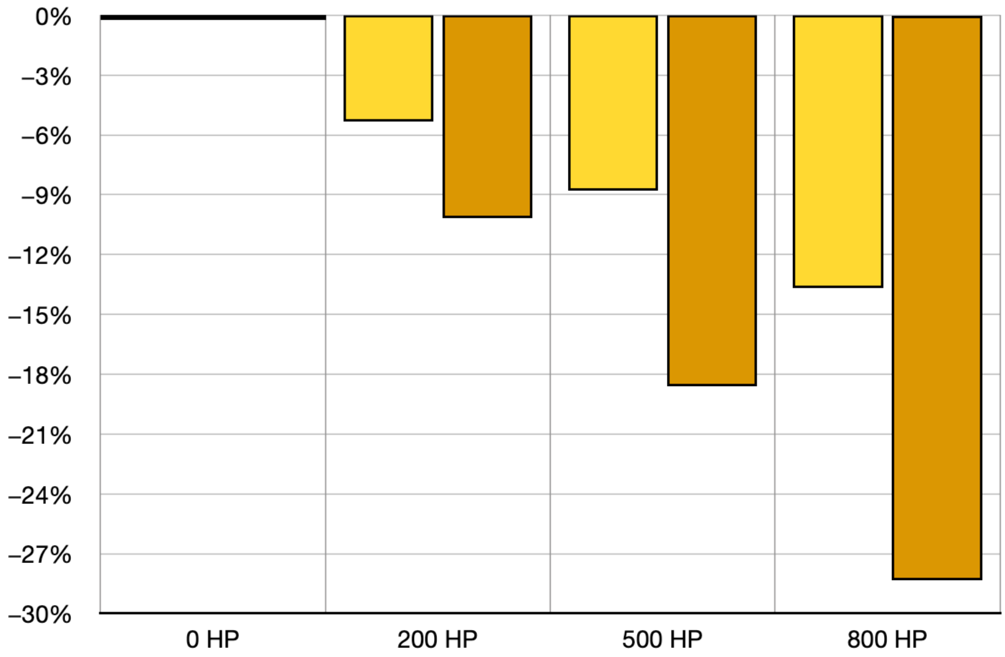

Figure 29. Relative change in emissions (%) with high electricity prices and different numbers of heat pumps. Relative change is in comparison with the case without heat pumps. Yellow bars represent the results with weight values $w_1 = 1$ and $w_2 = 0$ while orange bars represent the results with weight values $w_1 = 0$ and $w_2 = 1$.

In Figure 29, it can be seen that during the high electricity price in both situations, $w_1 = 1$ and $w_2 = 0$ as well as $w_1 = 0$ and $w_2 = 1$, when the number of heat pumps increases emissions decrease. Figure 29 also shows that in the situation where $w_1 = 0$ and $w_2 = 1$, emissions decrease significantly more in relation to the number of heat pumps compared to $w_1 =1$ and $w_2 = 0$. The reason for this is that only the minimization of emissions has been prioritized in the situations $w_1 = 0$ and $w_2 = 1$.

Figure 30 shows profits with 200, 500 and 800 HPs for low electricity prices. The blue bars illustrate 200, 500 and 800 HPs with weights $w_1 = 1$ and $w_2 = 0$ and the green bars illustrate the situation with weights $w_1 = 0$ and $w_2 = 1$ for 200, 500 and 800 HPs. The situation with $w_1 = 1$ and $w_2 = 0$, zero heat pumps and low electricity prices is used as a reference point for comparing other situations. The profits for this situation are €−920 380, which means 0% in this case.

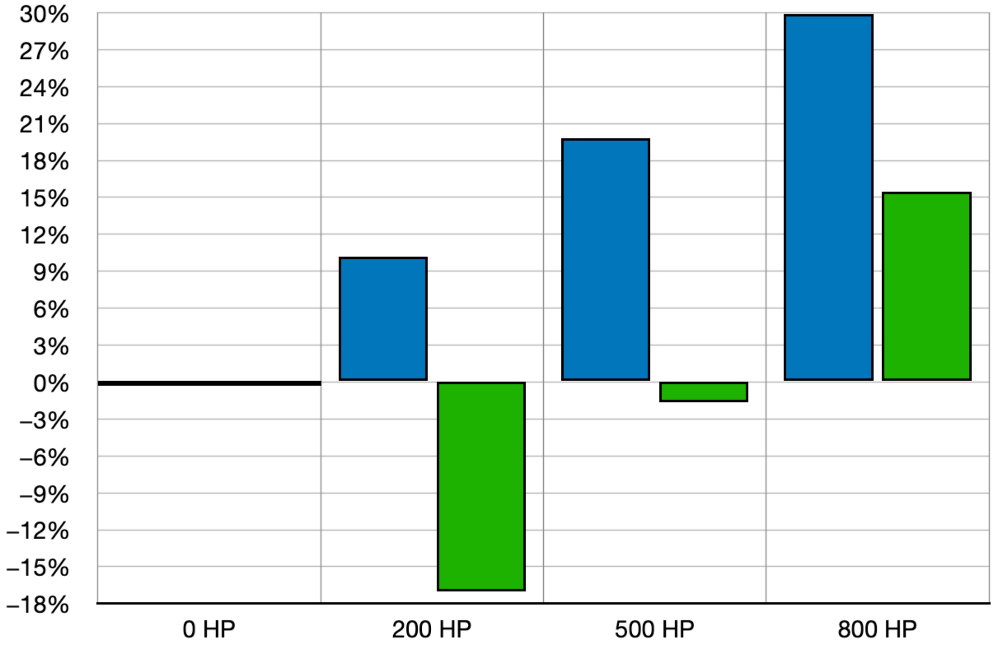

Figure 30. Relative change in profits (%) with low electricity prices and different numbers of heat pumps. Relative change is in comparison with the case without heat pumps. Blue bars represent the results with weight values $w_1 = 1$ and $w_2 = 0$ while green bars represent the results with weight values $w_1 = 0$ and $w_2 = 1$.

In Figure 30, during a period of low electricity prices in both situations, $w_1 = 1$ and $w_2 = 0$, as well as $w_1 = 0$ and $w_2 = 1$, when the number of heat pumps increases, more profits are gained. As an example, the profits with 200 HPs are smaller than with 800 HPs in both situations. However, it can be seen from Figure 30 that in the situation where $w_1 = 1$ and $w_2 = 0$, the profits of all the heat pumps (200, 500 and 800) are higher than in the reference situation. In a situation where $w_1 = 0$ and $w_2 = 1$ with 200 HPs, profits are smaller (−16.98%). In the same situation with 500 HPs profits are −1.67% smaller. However, when the number of heat pumps is 800, the profits are +15.48% higher than in the comparison situation.

Figure 31 shows emissions with 200, 500 and 800 HPs for low electricity prices. The yellow bars illustrate 200, 500 and 800 HPs with weights $w_1 = 1$ and $w_2 = 0$ and the orange bars illustrate the situation with weights $w_1 = 0$ and $w_2 = 1$ for 200, 500 and 800 HPs. The situation with $w_1 = 1$ and $w_2 = 0$, zero heat pumps and low electricity prices is used as a reference point for comparing other situations. Emissions for this situation are 3 392 742 kg, which means 0% in this case.

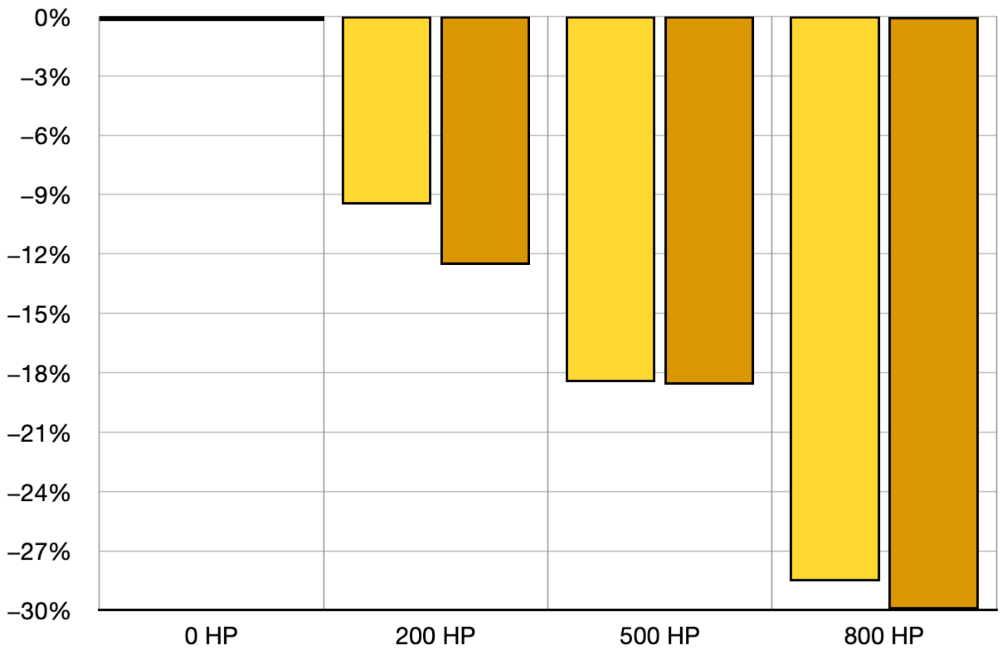

Figure 31. Relative change in emissions (%) with low electricity prices and different numbers of heat pumps. Relative change is in comparison with the case without heat pumps. Yellow bars represent the results with weight values $w_1 = 1$ and $w_2 = 0$ while orange bars represent the results with weight values $w_1 = 0$ and $w_2 = 1$.

Figure 31 shows that during a period of low electricity prices in both situations, $w_1 = 1$ and $w_2 = 0$, as well as $w_1 = 0$ and $w_2 = 1$, when the number of heat pumps increases, emissions decrease. In Figure 31, the difference between $w_1 = 1$ and $w_2 = 0$ and $w_1 = 0$ and $w_2 = 1$ is smaller than that in Figure 29.

6 DISCUSSION

The next step was to study which of these weight combinations were the most optimal solution for each different scenario. The results were compared with the percentages of relative change from Tables 5−12.

For scenario 1, Table 5 shows that when the goal is to find a solution that maximizes profits and minimizes emissions, the weight values $w_1 = 0.06$ and $w_2 = 0.94$ produce the most optimal solution. The profits would be +0.12% and emissions −0.35% than in the reference situation. If minimization of emissions were prioritized more, then the weight values of $w_1 = 0.04$ and $w_2 = 0.96$ would produce the most optimal solution. The profits would be 7.5% and emissions 1.5% less than in the reference situation. When comparing these two situations, the weights $w_1 = 0.06$ and $w_2 = 0.94$ are still the most optimal option since the profits are 8.3% higher than in the situation with $w_1 = 0.04$ and $w_2 = 0.96$. Emissions are 1.2% higher when $w_1 = 0.06$ and $w_2 = 0.94$ than in the situation where $w_1 = 0.04$ and $w_2 = 0.96$.

In scenario 2, Table 6 shows that when the goal is to find a solution that maximizes profits and minimizes emissions, the weight values $w_1 = 0.2$ and $w_2 = 0.8$ produce the most optimal solution. The profits would be 4.17% and emissions 3.4% less than in the reference situation. If minimizing emissions were prioritized more, then the weight values $w_1 = 0.18$ and $w_2 = 0.82$ would produce the most optimal solution. The profits would be 0.97% and emissions 4.18% less than in the reference situation. When comparing these two situations, the weights $w_1 = 0.2$ and $w_2 = 0.8$ are still the most optimal option since the profits are 3.2% higher than in the situation where $w_1 = 0.18$ and $w_2 = 0.82$. Emissions are 0.8% lower with $w_1 = 0.18$ and $w_2 = 0.82$ than in the situation where $w_1 = 0.2$ and $w_2 = 0.8$.

In scenario 3, Table 7 shows that when the goal is to find a solution that maximizes profits and minimizes emissions, the weight values $w_1 = 0.9$ and $w_2 = 0.1$ produce the most optimal solution. The profits would be 0.26% higher and emissions 6.85% less than in the reference situation. If minimizing emissions were prioritized more, then the weight values $w_1 = 0.8$ and $w_2 = 0.2$ would produce the most optimal solution. The profits would be 1.85% and emissions 7.39% less than in the reference situation. When these two situations are compared with each other, the most optimal solution is $w_1 = 0.9$ and $w_2 =$

0.1 since profits would be 2.16% higher than in the situation where $w_1 = 0.8$ and $w_2 = 0.2$. Also, after comparing the standard deviations, it is worth noting that the situation where $w_1 = 0.9$ and $w_2 = 0.1$ is still the most optimal solution for scenario 3.

In scenario 4, Table 8 shows that almost every situation meets the criteria for finding a solution to maximize profits and minimize emissions. However, one situation is much better than the other solutions, namely the weight values $w_1 = 0.3$ and $w_2 = 0.7$ produce the most optimal solution. The profits would be 8.64% higher and emissions would decrease 10.07% in the comparison with the reference situation. When $w_1 = 0.3$ and $w_2 = 0.7$, the standard deviations of profits and emissions would be almost the same as in the other optimization situations. Therefore, the results can be considered reliable.

In scenario 5, Table 9 shows that when the goal is to find a solution that maximizes profits and minimizes emissions, the weight values $w_1 = 0.98$ and $w_2 = 0.02$ produce the most optimal solution. The profits would increase 2.68% and emissions decrease 15.91% in the comparison with reference situation. This situation is by far the most optimal solution for scenario 5.

In scenario 6, Table 10 shows that when the goal is to find a solution that maximizes profits and minimizes emissions, the weight values $w_1 = 0.6$ and $w_2 = 0.4$ produce the most optimal solution. The profits would be 19.87% higher and emissions 18.56% less than in the comparison situation. If minimizing emissions were prioritized more, then the weight values $w_1 = 0.5$ and $w_2 = 0.5$ would produce the most optimal solution. The profits would be 19.33% higher and emissions 18.65% less than in the comparison situation. When comparing these two situations, the weights $w_1 = 0.6$ and $w_2 = 0.4$ are still the most optimal option since the profits are 0.7% higher than in the situation where $w_1 = 0.5$ and $w_2 = 0.5$. Emissions would be 0.11% higher when $w_1 = 0.6$ and $w_2 = 0.4$ than in the situation where $w_1 = 0.5$ and $w_2 = 0.5$.

In scenario 7, Table 11 shows that when the goal is to find a solution maximizing profits and minimizing emissions, situation $w_1 = 1$ and $w_2 = 0$ was the only optimal solution. The profits would be 1.37% higher and emissions 13.66% lower than in the reference situation. If minimizing emissions were prioritized more, then the weight values $w_1 = 0.94$ and $w_2 = 0.06$ would produce the most optimal solution. The profits would be 1.61% and emissions 26.57% lower than in the reference case. When comparing the two situations, both options are suitable. Which of these is better in relation to the situation depends on whether increasing profits is more significant than minimizing emissions. The standard deviations of profits and emissions were approximately the same, which is why they do not affect the results.

In scenario 8, Table 12 shows that when the goal is to find a solution that maximizes profits and minimizes emissions, the weight values w_1 = 0.7 and w_2 = 0.3 produce the most optimal solution. The profits would be 29.95% higher and emissions 28.57% lower than in the reference case. If minimizing emissions were prioritized more, then the weight values w_1 = 0.1 and w_2 = 0.9 would produce the most optimal solution. The profits would be 15.56% higher and emissions 30.35% lower than in the reference case. When the two situations are compared, w_1 = 0.7 and w_2 = 0.3 is still the most optimal solution. This is because in the situation where w_1 = 0.1 and w_2 = 0.9 profits are 20.5% higher than in the situation where w_1 = 0.1 and w_2 = 0.9. The standard deviation of emissions in the situation where w_1 = 0.7 and w_2 = 0.3 is twice as big as in situation where w_1 = 0.1 and w_2 = 0.9. This can affect the amount of emissions in the situation where w_1 = 0.7 and w_2 = 0.3. However, the profits in this situation are still much better than in the situation where w_1 = 0.1 and w_2 = 0.9. Thus, it can be concluded that w_1 = 0.7 and w_2 = 0.3 is the most optimal solution for scenario 8.

Based on Figures 28 and 30, it can be noted that increasing the number of heat pumps increases the amount of profits during a period of high electricity prices. During periods of low electricity prices, profits are negative, but the more heat pumps are integrated into the district heating network, the less loss there will be. Figures 29 and 31 also show that as the number of heat pumps increases, the amount of emissions decreases.

The production of district heating during the period of low electricity prices (situations where w_1 = 1), with 800 heat pumps integrated, generated 28.25% less emissions than a similar situation without heat pumps. With 500 heat pumps, the emissions were 18.47% lower and with 200 heat pumps 9.51% lower. From this, it can be estimated that during the period of low electricity prices emissions will be reduced by about 4% when 100 heat pumps are integrated into the district heating network. During the period of high electricity prices (situations where w_1 = 1), the production of district heating with 800 heat pumps integrated, generated 13.66% less emissions than without heat pumps. With 500 heat pumps the emissions were 8.79% lower and with 200 heat pumps 5.34% lower. From this, it can be estimated that during the period of low electricity prices emissions will be reduced by about 2% when 100 heat pumps are integrated into the district heating network.

When priority is given to minimizing emissions ($w_2 = 1$) during high electricity prices in district heating network that has 800 integrated heat pumps, generated 28.32% less emissions than situation without heat pumps. With 500 heat pumps, the emissions were 18.60% lower and with 200 heat pumps 10.19% lower. From this, it can be estimated that emissions will be reduced by about 3–5% when 100 heat pumps are integrated into the district heating network during high electricity prices. During low electricity prices in district heating network that has 800 integrated heat pumps, generated 30.2% less emissions than a similar situation without heat pumps. With 500 heat pumps, the emissions were 20.76% lower and with 200 heat pumps 12.55% lower. From this, it can be estimated that emissions will be reduced by about 3.5–6% when 100 heat pumps are integrated into the district heating network during low electricity prices.

For more reliable results, three simulations were performed with each of the weight values for scenarios with HPs. This was because HPs were randomly associated with 2956 different buildings. The more simulations there were with each weight value, the more reliable the result would be due to convergence of variation. However, due to limited time, three simulations each with a random selection of heat pumps were made for each of the weight values.

In addition, the accuracy and reliability of the results are influenced by the price of electricity. In this work, both high and low electricity prices were considered. The study could also have included average electricity prices and carried out the same optimizations for comparison.

7 CONCLUSIONS

The results showed that, for each simulated scenario, the optimal weight values were different. Therefore, it is difficult to establish a single optimal weight that would apply to all scenarios. For each scenario, efforts were made to find the most optimal weight values to increase profits and reduce emissions. The optimal weight values might differ if minimization of emissions were given higher priority.

Increasing the number of heat pumps in the building stock had a positive effect on maximizing profits and minimizing emissions. When electricity prices were high, the more heat pumps that were integrated into the district heating network, the more profit was generated. Similarly, during low electricity prices, the number of losses decreased as the number of heat pumps increased. According to the simulations, installation of heat pumps would also decrease the emissions related to energy production at city level. During high electricity prices emissions decreased 2% per 100 heat pumps and during low electricity prices emissions decreased 4% per 100 heat pumps when only profits are maximized. During high electricity prices emissions decreased 3–5% per 100 heat pumps and during low electricity prices emissions decreased 3.5–6% when only emissions are minimized.

8 SUMMARY

This master's thesis examined the district heating system and energy network of the future. The experimental part included a simulation for the multi-objective optimization of the Oulu district heating system with buildings included. From a production point of view, the aim of multi-objective optimization was to maximize profits and minimize emissions by identifying the related weight parameters in the objective function.

The experimental part was performed using MATLAB® software. The optimization simulator utilized in this work was developed by Dr Petri Hietaharju. First, 15 different multi-objective optimizations were made for both high and low electricity prices. These optimizations were considered without heat pumps. Subsequently, an examination was made of how the number of heat pumps affects the profits and emissions of DH production and the role of the weights in the objective function. Multi-objective optimization was carried out for both high and low electricity prices for a period of 48 hours.

For reliability, each optimization that included heat pumps was done three times. In these three optimizations, the values remained the same, but buildings with heat pumps were selected randomly. After multi-objective optimization, eight different tables were formed showing profits, emissions and relative change. Based on these tables, four figures were formed comparing the differences between profits and emissions of 200, 500 and 800 heat pumps with the zero heat pump situation.

For each situation, a different optimal solution was found. Therefore, it may be hard to establish a single most optimal solution that would apply to all situations, no matter how many heat pumps there are or what the price of electricity is.

Based on the results, it is worth noting that the number of heat pumps can play a significant role in maximizing profit and minimizing emissions. With high and low electricity prices, the more heat pumps that were integrated into the district heating network, the more profit was generated. As the number of heat pumps increased, total emissions also decreased by about 3% per every 100 heat pumps.

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