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Optimization of District Heating Systems for Future Uncertain Conditions

Deterministic and Stochastic Linear Modelling

Master's thesis in Sustainable Energy Systems

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Abstract

In Sweden, the demand for space heating and hot water is mainly supplied by district heating. Factors with high uncertainty, such as electricity price, heat demand, policies and climate strategies, affects the future development of district heating. The risks associated with these uncertainties must be managed while capitalizing on opportunities of improvements and optimization of the district heating system.

This thesis investigates to what extent uncertainty analysis is important for district heating system planning. To this end, this thesis investigates the sensitivity of operational patterns and investment choices of Swedish district heating systems to uncertainty in biofuel costs, electricity price, availability of industrial waste heat and the heat demand of the system. This is done by the development of two brownfield district heating system optimization models, a deterministic and a stochastic one in the modeling language GAMS. The models are linear and optimize investments and dispatch of three district heating type systems with respect to minimizing the annualized total system cost.

The conclusion is that technologies with low investment cost, mainly electric boilers, are favored when uncertainties are considered. In general, power-to-heat technologies are favorable to give the district heating systems the ability to adapt to the electricity and biofuel prices and to be cost-efficient in many future outcomes. The electricity production from combined heat and power units varies depending on the electricity price, at high electricity price combined heat and power units maximize their electricity production and at low electricity prices they refrain from up to 50% of the electricity production, in favor of producing additional heat. Furthermore, the sizing of thermal energy storage is sensitive to the uncertain parameters, resulting in different storage capacities depending on how the uncertainties affect the marginal value of heat. The value of accounting for uncertainties varies between the systems, and the system with a greater mix of technologies is less sensitive to the uncertainties applied. A risk has been identified that potential economic benefits can be missed out on if uncertainties are not considered, either by not meeting the demand due to lack of capacity or by not being able to capitalize on low electricity prices.

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Abbreviations

BG	Biogas
BO	Bio oil
CHP	Combined heat and power
COP	Coefficient of performance
DH	District heating
FLH	Full load hours
HOB	Heat only boiler
HP	Heat pump
PtH	Power to heat
TES	Thermal energy storage
VRES	Variable renewable energy sources
W	Municipal solid waste

Nomenclature

Sets

T	Total number of time steps
t	Set including all hours
N	Total number of heat generation units in the DH system
n	Set including all heat generation units
G	Total number of new heat generation units
g	Subset to n, including all new heat generation units
TES	The thermal energy storage
chp	Subset to n including only the CHP units

Parameters

C_{el}	Price of electricity [SEK/MWh_{el}]
C_{fuel}	The cost of fuel [SEK/MWh_{fuel}]
C_{inv}	Annualized investment cost [SEK/MW]
C_{PL}	Cost of running at part load [SEK]
C_{PLc}	Part load cost coefficient [SEK*h/MWh]
$C_{start\ up}$	Cost of start up [SEK/MW]
D	The heat demand [MWh/h]
$f_{min\ gen}$	Factor for minimum load level of a plant
η_{tot}	Total efficiency of the plant. Equal to η_{th} for non HOBs and COP for HPs.
η_{min}	Efficiency at minimum load level
η_{TES}	The charge and discharge efficiency of the TES
Q_{max}	Heat generation capacity of existing units. [MW]
r_c	The c-rate of the TES [1/h]
TES_{loss}	Factor for energy losses in the TES [MWh/h]

Variables

C_{tot}	The total annual cost of the DH system [SEK/yr]

Positive Variables

E	Total energy produced, i.e. heat and electricity [MWh]
I	Investment capacity for new units [MW]
P	Electricity produced [MWh/h]
Q	Heat generation [MWh/h]
Q_{spin}	Fictive variable used to account for start up and part load costs [MW]

Q_{on}	Fictive variable to account for changes in Q_{spin} [MW]
Q_{max}	Maximum capacity of an existing unit [MWh/h]
Q_{min}	Minimum load factor of a production unit
R	Refraining from electricity production to increase heat generation [MWh/h]
TES_{ch}	Charging of the TES [MWh/h]
TES_{dch}	Discharging of the TES [MWh/h]
TES_{level}	The energy level of the TES [MWh]

1 Introduction

District heating (DH) is a large-scale method for production and distribution of heat, where the heat is produced in one or several centralized production sites and is distributed through a pipe system to the consumers. District heating is a resource efficient technique to provide heat for space heating and hot tap water. In Sweden the use of district heating accounted for 57% of the supplied heat for space heating and hot tap water in 2016 (Energimyndigheten, 2017). District heating is locally bound, since heat losses and pump work are increased with increasing distribution distances making DH inefficient in rural areas. There is thus often one DH system for each city or town where there is a demand for heat. There are approximately 500 DH networks in Sweden and the different networks vary considerably in size, geographical location and heat production technologies (Energiföretagen, 2021). Traditionally, district heating has been produced via combustion in thermal plants, such as heat only boilers and combined heat and power plants, but the future development of the district heating sector is uncertain. There is a potential need for new investments in the district heating sector since existing units might need to be replaced and since utilizing new technology types can reduce costs. Factors such as electricity price, heat demand, policies and climate strategies can affect which investments are made and how facilities are operated in the future. A challenge for the district heating companies is to ensure that the DH system has long-lasting economical and operational robustness in an uncertain future. Investments made today will last for a long time, thus, they must be a good solution also in possible future scenarios.

With the integration of variable renewable energy sources in electricity systems, the price of electricity is expected to become more volatile. This change might have a direct effect on the district heating systems, since there are units that consume electricity, and units that can produce electricity in a DH system. Hence, the electricity price is an important factor for the competitiveness of units in DH systems that interact with the electricity market, as changes in the electricity price can affect their operational cost. As it is difficult to predict what the electricity price will be in the future, it is an important uncertainty to take into consideration when making investment decisions in DH systems.

There are further uncertainties in future energy systems, regarding the availability and price of biomass and industrial waste heat. With the current decarbonizing and climate policies, the availability of industrial waste heat supply for DH might decrease since industries could need to utilize their heat on site, e.g. for carbon capture and storage technologies (Bui, et al., 2018) in order to decrease their own greenhouse gas emissions. For systems with industrial waste heat, this can have an impact on the current merit order and the total cost of the system, since low-cost heat supply needs to be replaced with new base load capacity. In the future, the price of biomass might change if the demand for biomass increases (Sandin, Sahlén Zetterberg, & Rydberg, 2019), as a consequence of climate policies to reduce the global use of fossil fuels. The cost of biomass is therefore an uncertainty in the future of Swedish DH systems, as the operational cost of many existing and new units are dependent on the cost of biomass.

Energy system modeling is a tool that can be used to support planning of operational and investment decisions in district heating systems. Representing uncertainty in energy system modeling is a common problem and can be handled with various methods. A common method of accounting for uncertainty is the usage of deterministic models and sensitivity analysis. In deterministic models the uncertain parameters are assumed to be known and provided exogenously to the model, and by implementing sensitivity analysis the understanding of how individual parameters affect the output can be enhanced (Gjorgiev, Sansavini, & Crespo Del Granado, 2017). Uncertainty in energy system modeling can also be represented by stochastic modeling. In stochastic models, different scenarios are defined with probabilities for parameters which are considered stochastic in nature in order to incorporate parameters which depend on future external factors. There is a structural difference between deterministic and stochastic models, as stochastic models consider multiple possible outcomes of parameters and are implicitly risk-minimizing (Gjorgiev, Sansavini, & Crespo Del Granado, 2017), whereas deterministic models show individual parameter effects. Due to the structural difference between the methods, stochastic models are in general more computationally complex and less frequently used as it is difficult to estimate probabilities of different outcomes.

Together, the multiple sources of uncertainty connected to DH systems creates an environment that can be difficult for an energy company to navigate. Energy companies need to provide reliable and cost-effective supply of district heating to their customers. To do this, uncertainties that could affect the security of supply and costs of the DH system needs to be understood. Then opportunities of improvements can be capitalized on without large economic risk. How different units in a DH system affect each other under different circumstances is thus an important issue to understand and to do this knowledge is needed about how uncertainties can be handled in DH systems planning.

1.1 Aim

The aim of this thesis is 1) to investigate methods to handle uncertainties in DH system planning, and 2) to apply these methods to identify which types of DH investments are robust for future systems based on dispatch of units and total system cost. The work considers future investments in three existing Swedish DH systems. The thesis investigates the sensitivity of investment choices, operational patterns, and total system cost to uncertainty in biofuel costs, electricity price, availability of industrial waste heat and the heat demand of the system. Further, the risk on total system cost associated with not including uncertainties in investment and operational decisions is estimated. Trends and differences in optimal investments and operation between the investigated systems are identified.

2 Background

In this section, relevant background information is presented in short. In 2.1, a background of investment decision making is presented. In 2.2, heat production technologies are presented. In 2.3, an overview of the current DH systems in Sweden is given. In 2.4, external factors affecting district heating systems are introduced and finally in 2.5 the modeling methods used are presented in a general form.

2.1 Investment Decisioning and District Heating Economics

In order to have a district heating system, heat producing units are required. The costs associated with a production unit can be divided into two parts, investment cost and operational cost. The size of the investment cost is proportional to the capacity of the production unit, and the operational cost describes the cost to produce one unit of heat. In most cases, production units with a higher investment cost have a lower operational cost. District heating companies want to minimize the total system cost, meaning that they need to assess whether a unit with a higher investment cost is better or worse than a unit with lower investment cost, in order to reduce the operational cost.

In district heating systems with existing heat production units, the investment costs can be considered sunk costs, since the investments have already been made. When the heat demand needs to be met, the only relevant cost is the operational cost of the units, thus, the units with the lowest operational cost are prioritized to produce heat. The order in which units are dispatched in a system is called the merit order and the low-cost units in a system place the lowest in the merit order of the system. In Figure 1, a simplified load duration curve of a district heating system is visualized. Typically, a unit with low operational cost would produce heat for the base load, since capacity is required for many hours, making the higher investment cost worthwhile. For the peak load the operational cost is less important relative to the investment cost due to the few production hours. This results in peak load units typically having a lower investment cost and higher operational cost.

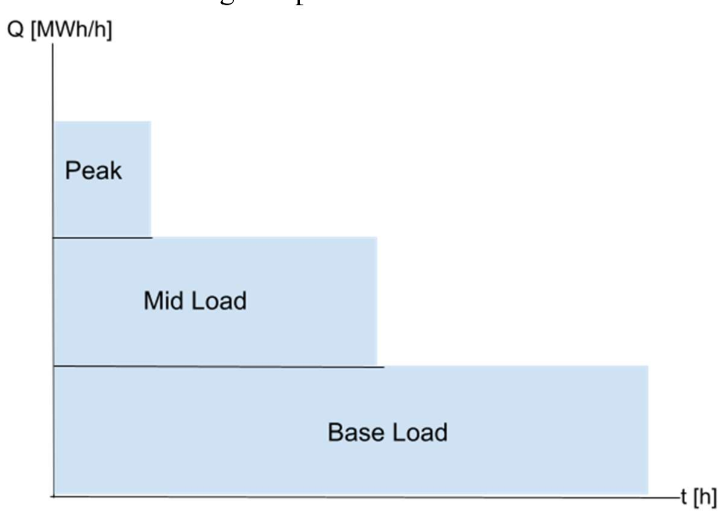

Figure 1: A simplified overview of a merit order in the form of a heat load duration curve.

In an DH system, existing units can have higher operational costs than a new unit would have. For such a system to make an investment, the total savings from the decreased operational costs of the system must be larger or at least as big as the investment cost of the new unit. The optimal size of a new unit is determined by where the equilibrium between the increased investment costs and decreased operational costs minimize the total system cost.

2.2 Technologies in District Heating Systems

Figure 2 presents a general overview of a DH system with different heat generation technologies and storage. By having different types of units in a DH system, the heat demand can be supplied for different demand levels while keeping the total system cost as low as possible. In this section, common technologies used and their role in DH systems are briefly described.

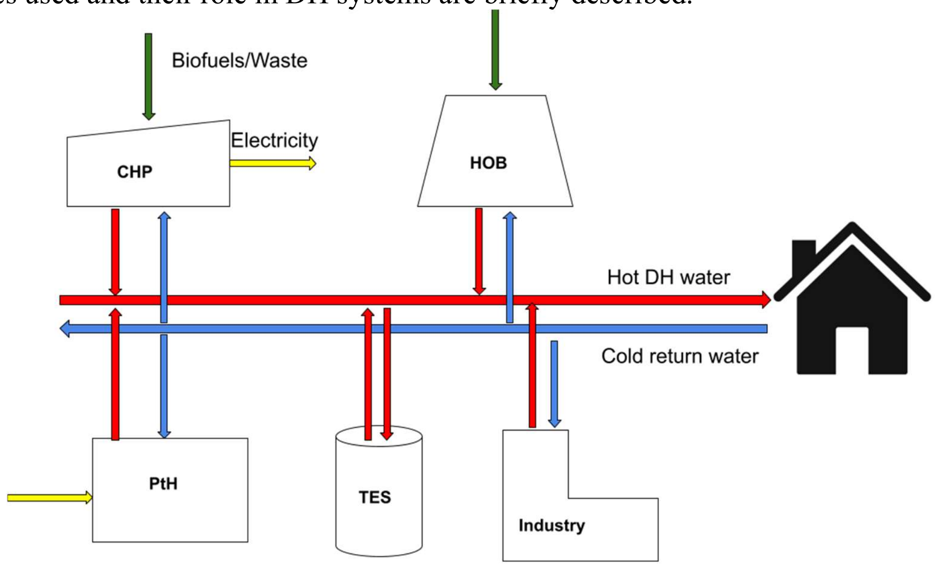

Figure 2: A general overview of a DH system with different heat generation technologies with fuel inputs and thermal energy storage. CHP = Combined Heat and Power, HOB = Heat Only Boiler, PtH = Power-to-heat, TES= Thermal Energy Storage, Industry = Industrial waste heat.

2.2.1 Heat Only Boiler

A common technology used for the heat production in a DH system is a heat only boiler (HOB). It is a unit where fuel is combusted in a boiler, and the heat released is transferred to an internal energy carrier (typically water) which is then coupled to the DH network via a heat exchanger (The Danish Energy Agency, 2016). HOB plants have high efficiency and depending on which fuel is used a HOB can have different characteristics. If a HOB uses gas, oil or bio oil it is typically only used at peak hours when the demand is large since they have an expensive fuel cost but are cheap in investment cost. If a HOB uses cheaper fuels like municipal solid waste or wood chips they are typically used more as a base load unit, as they have lower variable cost, but higher investment costs.

2.2.2 Combined Heat and Power

Combined heat and power (CHP) plants are similar to HOBs but with the difference that they produce electricity and heat simultaneously. In order to produce electricity, a steam turbine and an electricity generator is needed which increases the investment cost of the plant, but by selling the produced electricity the operational cost can be decreased, making it suitable as a base load unit. CHP plants have a high total efficiency and can use different fuels, such as biomass or municipal solid waste (The Danish Energy Agency, 2016). Many CHP plants have the flexibility to refrain from electricity production, in favor of increased heat production.

2.2.3 Power-to-Heat Technology

Another heat generation option is power-to-heat technologies (PtH) i.e. using electricity to produce heat. This is mainly done with two technologies, heat pumps (HP) and electric boilers (EB). An electric boiler uses electricity directly to produce heat, having efficiencies close to 1 and relatively low investment costs (The Danish Energy Agency, 2016). HPs use electricity in order to utilize low grade heat from e.g. sewage- or sea water to generate useful heat at temperature levels suited for district heating. A HP can have a coefficient of performance (COP) of 3-4, meaning that for 1 unit of electricity 3-4 units of useful heat are generated. Heat pumps are thus very efficient, but they have an increased investment cost compared to the electric boilers (The Danish Energy Agency, 2016).

2.2.4 Thermal Energy Storage

Thermal energy storage (TES) allows heat to be stored and used later and can thus decrease the usage of more expensive peak load units (Cabeza, 2012). There are different types of TES with different characteristics in terms of (dis)charge-rate and sizes. There are TESs suited for seasonal storage as well as TESs storing heat for only a few hours. Examples of seasonal storage technologies are pit-storage or borehole-storage, which have a low charge- and discharge-rate relative to their size. An example of an intermediate storage is a large scale hot water tank which can help during peak hours to smoothen the heat production, but also store heat over longer periods up to a couple of weeks (The danish Energy Agency, 2020).

2.3 District Heating in Sweden Today

The current Swedish DH systems use a wide range of technologies including heat pumps, heat only boilers and combined heat and power plants. Many systems also utilize industrial waste heat. Figure 3 shows the fuel usage in 2019 for district heating purposes in Sweden. In 2019, biofuels and municipal solid waste were the most common fuels and provided 65% of the energy (Energiföretagen, 2021). There is, however, still some use of fossil fuels which have not been phased out in some of the DH systems with the main use being peak capacity.

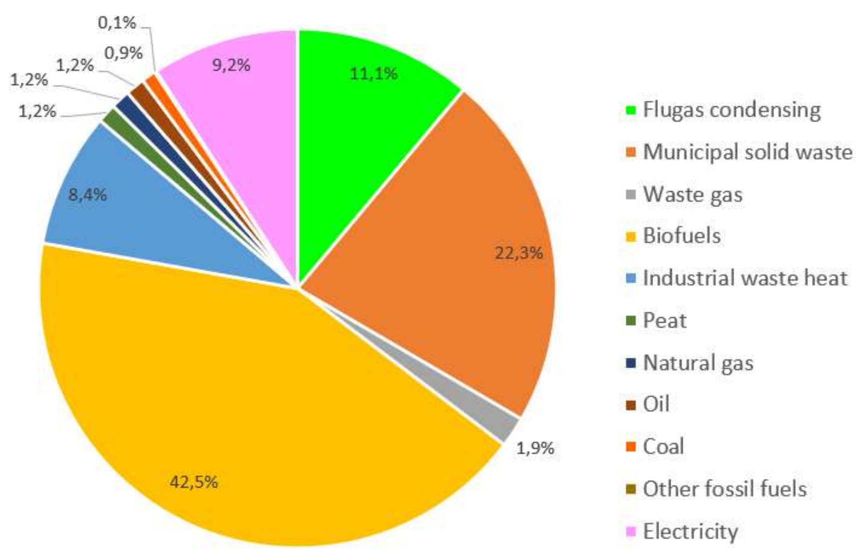

Figure 3: The fuel use in district heating systems 2019. Based on data from Energiföretagen (Energiföretagen, 2021).

As a part of this thesis work, a database was created listing many of the larger DH networks in Sweden to get an overview of which technology mixes that exist. The database includes the capacities of production units, fuel usage and total energy deliveries. This database is a base for the whole project since it gives an understanding of the current situation. The data was mainly collected through the energy companies' websites and by contacting the energy companies directly. In Figure 4, the share of the total installed capacity per fuel type unit is presented for 48 large district heating systems in

Sweden. In the figure there is a significant amount of capacity reliant on fossil oil. These units are typically quite old and might need to be replaced in the coming years to be in line with climate targets. By looking at 48 of the largest district heating systems a categorization of the system based on their installed capacity could be done. 9 networks mainly consist of heat only boilers. 24 networks consist of a mix of heat generation technologies, including HOBs, CHPs and Power-to-heat technologies. 15 networks consist of mainly CHPs and small amounts of peak generation.

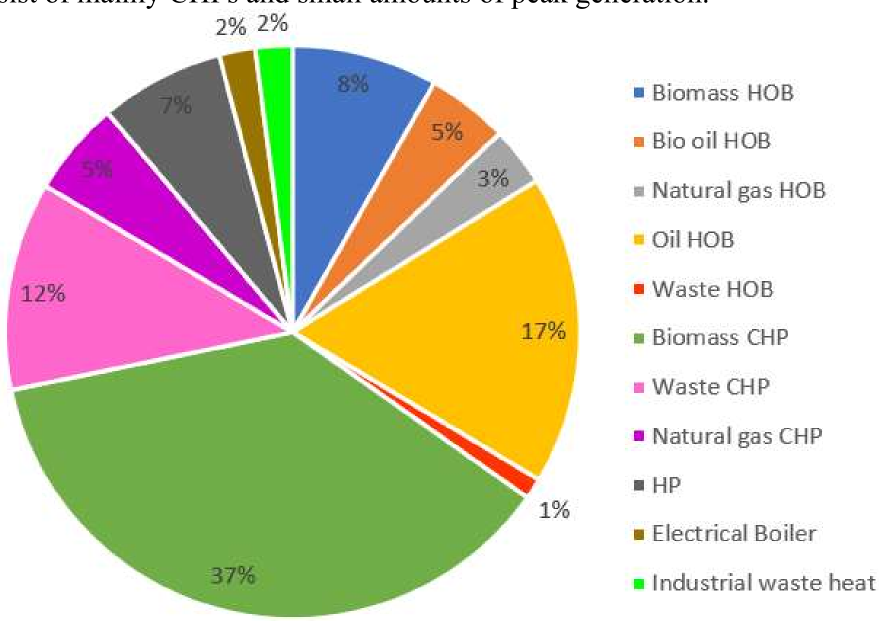

Figure 4: The share of the total installed capacity per fuel type unit for 48 large Swedish district heating systems.

2.4 External System Development

There are several external factors affecting the future development of district heating. Here, the most important ones are briefly described to give the reader a context to why the effect of these external uncertainties are further analyzed in the thesis.

2.4.1 Electricity System

The electricity market in Sweden is changing with an increasing amount of variable renewable energy sources (VRES), mainly in the form of wind power and solar PV, and the potential phase-out of nuclear power. This is likely to lead to an increasing volatility of the electricity price dependent on how large share of the electricity that comes from VRES at a certain time (Romanchenko D. , Odenberger, Göransson, & Johnsson, 2017). The electricity price in Sweden from year to year is also dependent on the weather. In Sweden there is a significant amount of hydro power where annual precipitation levels affect the price by regulating the amount of available hydro power. Also, with increasing amounts of wind power the weather will affect the electricity price depending on how much the wind blows during a year. Finally, the demand for electricity is (to an extent) indirectly dependent on air temperature due to electricity being used for space heating (approximately 20% of the total electricity usage (Energimyndigheten, 2020)) meaning that annual average temperatures can have an impact on the electricity price (Energimyndigheten, 2019).

As there are units in DH systems that consume and produce electricity, potential changes of the electricity price might affect their role in the energy system. Power-to-heat technologies together with

TES can have a cost effective synergistic function with a more volatile electricity generation system, e.g. to reduce wind power curtailment by utilizing low-cost electricity (Bloess, Schill, & Zerrahn, 2018) to produce heat and charging the TES when electricity price is low. If the electricity price becomes high, PtH units can stop or reduce their production in favor of discharging the storage.

With an increased volatility of the electricity price, the value of controllable electricity production from CHP plants might become increasingly valuable for the electricity system and the local power balance (Profu, 2019). Historically, the revenues from electricity generation sales from the CHP plants has been considered a bonus income in addition to heat sales which is typically the prioritized product. Since the revenues from CHP plants are dependent on the electricity price, CHP plants might shift towards operating more based on the electricity demand rather than solely on the heat demand if the electricity price becomes more volatile (Profu, 2019). In summary, a change in electricity prices can impact the competitiveness of units in DH systems connected to the electricity system and, thus, the merit order of the DH system.

2.4.2 Biomass Resources

In Swedish district heating systems, biomass is a commonly used fuel for both CHPs and HOBs. This means that the economy of district heating systems will be impacted by the future cost of biomass and its availability. In a report from 2019, the Swedish environmental research institute concluded that the availability of biomass in Sweden is expected to increase to 2030 and afterwards (Sandin, Sahlén Zetterberg, & Rydberg, 2019). The demand for biomass is also expected to increase e.g. in material production or in biorefineries to produce chemicals (Takkellapati, Li, & Gonzalez, 2018). With a potential future increased demand of biomass, the prices of biomass-based fuels might rise, leading to increasing operational cost of units with biomass-based fuels. The increased operational cost of biomass fueled units could impact their competitiveness in the DH system, in favor of other heat generation options. However, in district heating production, low-grade biomass can be used that few others want to use (Krook Riekkola, Wetterlund, & Sandberg, 2017). This low-grade biomass might thus experience less competition and not increase in price, while other higher-grade biomass might experience competition driving prices higher.

2.4.3 Heat demand

The Swedish district heating production has expanded for a long period of time, however, the district heating growth rate is gradually decreasing because of energy efficiency measures in buildings and households (Sköldberg, Unger, & Holmström, 2015). As a result of this, Sköldberg et al. conclude that the Swedish district heating demand will stagnate or even be reduced in the future. On the other hand, there are also indications that the demand for district heating can increase in the coming years. For example, Steen et al. conclude that there is a potential demand for district heating in industrial processes as an approach to cost-efficiently reduce the need for fossil fuels (Steen, Sagebrand, & Walletun, 2015). The heat demand is also dependent on the ambient temperature, and therefore the district heating demand can vary on an annual basis. With future predictions of both increasing and decreasing demand of district heating, this is an uncertainty that needs to be considered in order to cost-effectively deliver heat to meet different possible demand levels.

2.4.4 The Accessibility of Industrial Waste Heat

Industrial waste heat can be defined as “excess energy that cannot be utilized internally and where the alternative is that the heat is released to the environment” (Byman, Rydstrand, Ilskog, & Åkesson, 2005). Industrial waste heat is utilized for district heating purposes and in 2019 the total share of industrial waste heat in the Swedish district heating systems was 8 % (Energiföretagen, 2021). This utilization is an energy efficiency measure for the district heating systems, as it decreases the need for external fuels to provide heat.

To meet climate targets, an important aspect is to decrease the greenhouse gas emissions from industrial processes and a promising strategy is to implement carbon capture and storage (CCS) technologies to reduce CO2 emissions on site. The application of CCS technologies in industries can have an effect on the accessibility of industrial waste heat for district heating purposes, as several of the CCS technologies are energy demanding (Cabeza, 2012). As industries in general always strive for further energy efficiency measures, there are possibilities that the industrial waste heat can be used "in house" e.g. for drying purposes or as a measure to reduce the usage of fossil fuels (Byman, Rydstrand, Ilskog, & Åkesson, 2005). For systems with industrial waste heat, this can have an impact on the current merit order and the total cost of the system, since low-cost heat supply needs to be replaced with new base load capacity.

2.5 Treatment of Uncertainty in Optimization Models

Uncertain parameters are important aspects of energy system modeling and hence methods for handling uncertainties are needed. In this section the two different modeling approaches applied in this work are briefly presented: deterministic and stochastic modeling.

A deterministic model is a model that always generates the same output for a certain input i.e. there is no randomness involved and the future can be considered as "known" (Gjorgiev, Sansavini, & Crespo Del Granado, 2017). In Figure 5 a general overview of a deterministic model is visualized. In real life problems, randomness often influences possible outcomes, and a commonly used way to analyze the impact of randomness in a deterministic model is to perform a sensitivity analysis. Sensitivity analysis is a method where the model is solved for different values of the input parameters, in order to analyze the sensitivity of the output relative to the input (Pichery, 2014).

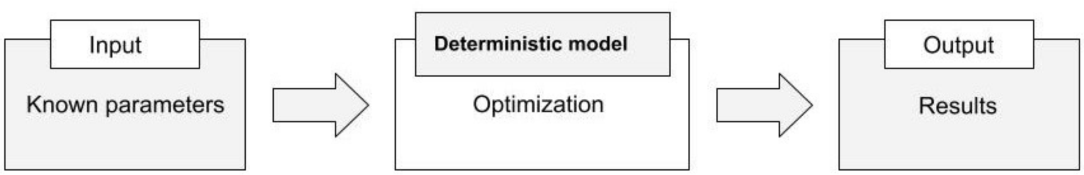

Figure 5: General overview of a deterministic model.

Stochastic programming is a mathematical approach to account for uncertainties in optimization models (Shapiro & Philpott, 2007). One of the most common stochastic programs is the two-stage linear program. In Figure 6, an overview of a general two-stage stochastic model is shown. The basic idea with the two-stage approach is that variables can be classified into two types; here-and-now variables and wait-and-see variables. The first type refers to the decision variables which need to be determined before realization of uncertain parameters, and the second type refers to the decision variables that are to be determined after the revealing of the uncertain parameters. Hence, the decision making regarding the here-and-now variables occurs in an initial stage and the decision making regarding the wait-and-see variables in a second stage (Shapiro & Philpott, 2007). The uncertain parameters will together form a set of possible scenarios. The stochastic parameters can either have discrete probabilities or a probability distribution that is used to weight the scenarios when calculating the expected value of the second stage problem. Hence, the model optimizes the first stage decision in order to perform averagely best for all scenarios relative to their likelihood.

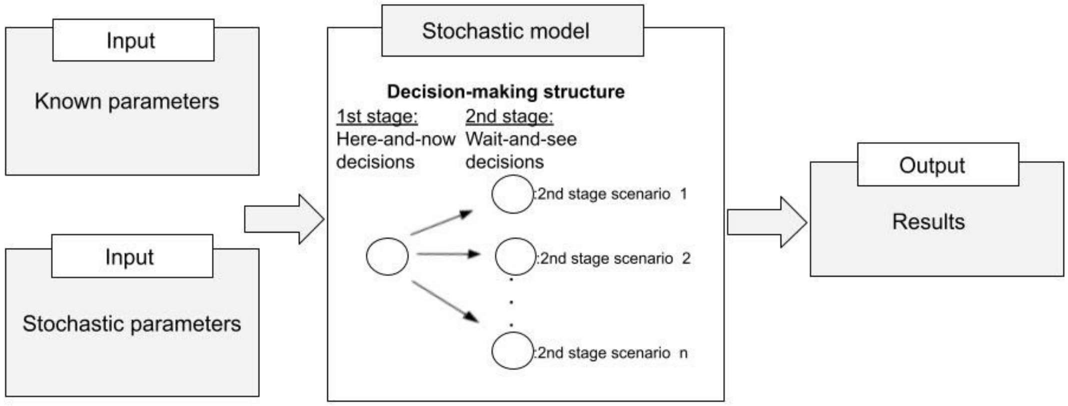

Figure 6: Overview of a general two-stage stochastic model set-up. The input data consists of known parameters and stochastic parameters with a known probability.

The two modeling methods have both advantages and disadvantages. Stochastic models are in general more computationally demanding and the considered scenarios increase exponentially with the number of stochastic variables. Stochastic models are less frequently used compared to deterministic models, since it can be difficult to estimate probabilities of different outcomes. The results of a stochastic model, however, are more robust since it considers multiple scenarios, minimizing the risk of unexpected outcomes by optimizing the expected value. In deterministic models, only individual effects are considered, and therefore there is a potential risk of over-optimizing systems for specific cases, in ways that do not perform well under other circumstances.

3 Method

The method is divided into three main parts. In the first part, a core DH model is developed which is used to describe the dynamics and limitations of DH systems. The core model is a linear programming cost-minimizing investment and dispatch model. The model covers one year with a time resolution of one hour and is developed in the modeling language GAMS. In the second part, the core model is used in a deterministic set-up. A sensitivity analysis of fuel cost, heat demand, and availability of industrial waste heat is conducted to investigate the impact of individual uncertainties on DH systems. In the third and final part, the core model is used in a stochastic set-up, where the electricity price and heat demand are treated as stochastic parameters, to investigate the impact of multiple uncertainties simultaneously on DH systems.

The time scope of the analysis is year 2030 and since many existing units are likely to still be in use by then, this analysis is a brownfield analysis. As a base for the brownfield analysis, three type systems in Sweden are used, which are defined in section 3.1.2. The optimization of the three systems is evaluated in terms of investment, operations and total system cost, and the key performance indicators are the capacity of investment, full load hours of production units and the electricity production of the CHP units.

3.1 District Heating System Optimization Model

In this section the mathematical formulation of the core model is presented. The techno-economic data used in the model is defined in section 3.1.2 and this input data remains constant in both the deterministic and stochastic model set-ups.

3.1.1 Mathematical Formulation of the Core Model

The objective function of the model is to minimize the total system cost and is calculated according to equation 1. The objective represents the total cost of heat production, while accounting for profits from sold electricity generation from CHP units. The total cost function consists of several terms, i.e., fuel costs, fixed variable costs, part-load costs, start-up costs for the units and annualized costs of investments. All nomenclature in the following equations is explained in the notation list.

$$C_{tot} = \sum_t^T \sum_n^N \left(\frac{E(t,n) \cdot C_{fuel}(n)}{\eta(n)} + C_{PL}(t,n) + C_{start\,up}(t,n)\right) + \sum_t^T \sum_n^N Q(t,n) \cdot C_{var}(t,n) + \sum_g^G C_{inv}(g) \cdot I(g) + \sum_{TES} C_{inv}(TES) \cdot I(TES) - \sum_t^T \sum_n^N P(t,chp) \cdot C_{el}(t) \quad (1)$$

The objective function is bounded by several constraints. The demand constraint, which is calculated according to equation 2, ensures that the sum of heat generation from all units including charge and discharge from the TES, is equal to or larger than the heat demand at time t.

$$D(t) \leq \sum_n^N Q(t,n) + \sum_n^N R(t,n) + TES_{dis}(t) - TES_{ch}(t) \quad (2)$$

The maximum heat output constraint for existing units is defined in equation 3. This constraint ensures that existing heat generation units cannot exceed their installed capacities. Q is a positive variable and can thus never be less than zero, since a heat generation unit can never produce a negative amount of heat.

$$Q(t,n) \leq Q_{max}(n) \quad (3)$$

For the new investments, a similar constraint is added, defined in equation 4. Here I is not predefined but is the variable representing the capacity of the new investment.

$$Q(t,g) \leq I(g) \tag{4}$$

The electricity output from CHP units is bounded by the power-to-heat ratio (alpha) and is calculated according to equation 5. In this model, the CHP units are allowed some flexibility in their generation by refraining from electricity generation in order to increase their heat generation with the same amount. This feature is represented by the variable R which is calculated according to equation 6. The total energy output can thus be calculated according to equation 7 and for non-CHP units the energy output is equal to the heat output.

$$P(t,chp) = alpha(chp) \cdot Q(t,chp) - R(t,chp) \tag{5}$$

$$R(t,chp) \leq alpha(chp) \cdot Q(t,chp) \tag{6}$$

$$E(t,n) = Q(t,n) + P(t,chp) + R(t,chp) \tag{7}$$

In order to account for cycling properties the variable Q_{spin} denotes capacity which is active and available for generation in each technology for each time step according to previous work from (Göransson, Goop, Odenberger, & Johnsson, 2017).

$$Q(t,n) \leq Q_{spin}(t,n) \tag{8}$$

$$Q(t,n) \geq Q_{spin}(t,n) \cdot Q_{min}(t,n) \tag{9}$$

By tracking the change in Q_{spin} with Q_{on} according to equation 10, the startups of a production unit can be tracked, and costs considered.

$$Q_{on}(t,n) \geq Q_{spin}(t-1,n) - Q_{spin}(t,n) \tag{10}$$

The part load cost and startup cost for each unit is approximated according to equation 11 and 13 respectively. C_{PLc} is the cost coefficient for the linear interpolation of the part load cost and is calculated using equation 12.

$$C_{PLc}(n) = \frac{1}{(1-f_{min.gen}(n))} \cdot \left(\frac{C_{fuel}(n)}{\eta_{min}(n)} - \frac{C_{fuel}(n)}{\eta_{tot}(n)}\right) \tag{11}$$

$$C_{PL}(t,n) \geq C_{PLc}(n) \cdot (Q_{spin}(t,n) - Q(t,n)) \tag{12}$$

$$C_{start\,up}(t,n) \geq Q_{on}(t,n) \cdot C_{start,par}(n) \tag{13}$$

In previous work, Q_{spin} is assumed to represent a technology aggregate so that Q_{spin} can have any value between zero and the maximum capacity. Here it is used primarily for single plants, where Q_{spin} in reality only can be zero or equal to the capacity of the plant. This means that cycling costs are underestimated since the plants are modeled with increased flexibility compared to real operation, but the model will still pay some respect to the cycling costs compared to not using this method at all.

The TES needs additional equations from the production units since its operation is dependent on the previous time step. The storage level of the TES is limited by its size and this constraint is defined in equation 14, which ensures that the maximum level is never greater than the size of the TES. Since the energy level in the TES is defined as a positive variable it can never be lower than zero. The energy level of the storage at each hour is determined with equation 15. This equation relates the energy level of each hour to the previous one while taking charging and discharging of the storage into account as well as losses. Two different sources of energy losses in the TES have been accounted for. In equation 15 the last term accounts for losses to the surroundings of the TES and they are assumed to be constant and linearly proportional to the size of the TES. Also, the TES have a charge and discharge efficiency, η_{TES}, that generate losses when energy is charged to or discharged from the TES.

$$TES_{level}(t) \leq I_{TES}(TES) \tag{14}$$

$$TES_{level}(t) = TES_{level}(t-1) + TES_{ch}(t) \cdot \eta_{TES} - \frac{TES_{dis}(t)}{\eta_{TES}} - I(TES) \cdot TES_{loss} \tag{15}$$

Charging and discharging of the TES is limited by the c-rate of the TES. The c-rate is a measure of how much time a full charge or discharge of the storage takes. The charge and discharge rate constraints are defined in equations 16 and 17 respectively.

$$TES_{ch} \leq I(TES) \cdot r_c \tag{16}$$

$$TES_{dis} \leq I(TES) \cdot r_c \tag{17}$$

A final constraint for the TES sets the energy level of the first hour equal to the last one according to equation 18. This ensures that the ingoing energy at hour 1 is “paid for” while keeping the possibility to save energy across years.

$$TES_{level}(1) = TES_{level}(8760) + TES_{ch}(1) \cdot \eta_{TES} - \frac{TES_{dis}(1)}{\eta_{TES}} - I(TES) \cdot TES_{loss} \tag{18}$$

3.1.2 District Heating System Description

In this section the shared input data for the deterministic and the stochastic model is presented. Three types of theoretical district heating systems are analyzed, which are based on the plant portfolio of DH systems in Finspång, Västerås and Gothenburg. The DH systems existing thermal generation units and capacities are presented in Table 1, 2, and 3, respectively. Each DH system is selected from the DH network database, in order to represent a variety of common system types, in terms of existing heat generation units. Finspång represents systems which only consist of HOBs and industrial waste heat, denoted System HOB. Västerås represents systems which only consist of CHPs, called System CHP. Gothenburg represents systems with a mix of different heat generation technologies, called System Mix. The model does not allow for use of fossil fuels, hence the fossil fuels which are currently utilized in some of the existing systems have been substituted to biomass based ones with the assumption that the unit is not affected in any other regard than fuel cost.

For each system, the models can choose several heat generation investment alternatives and a TES investment, with the corresponding technical and cost data presented in Table 4 and Table 5, respectively. Even though the systems might have sufficient existing capacities to meet the peak demand, investment in new heat generation capacity can potentially decrease the total system cost as new generation units can have lower total cost than older units. Another reason for making new investments is that old units might need to be replaced, but this is not considered in this work. Existing installations of TES in the DH systems are neglected in order to analyze the optimal size of the storage for each system, but also to compare the investment in TES between the systems. All investment data is based on the Danish Energy Agencies catalogue (The Danish Energy Agency, 2016). The exchange rate from EUR to SEK is assumed to be 10 SEK/EUR and the discount rate is assumed to be 7%. The restriction of fossil fuels also applies to new investments, thus the fuels in the available investment alternatives are all non-fossil. The former investment in the existing units in each system is regarded as a sunk cost and is therefore not included in this mode

*Table 1: Technical data for existing heat generation technologies in system HOB. Based on Finspångs Tekniska Verk (Finspångs Tekniska Verk, 2020). *: changed to biobased from fossil fuel.*

Network	Unit Name	Unit Type	Fuel	Q [MW_{th}]	Q [MW_{el}]	Efficiency
System HOB	HOB W	HOB	Municipal Waste	10	-	0.9
	HOB B	HOB	Wood chips	14	-	0.9
	HOB BO	HOB	Bio oil*	39.5	-	0.9
	SSAB		Waste heat	3,4	-	1

Table 2: Technical data for existing heat generation technologies in system CHP. Based on contact with Mälarenergi (M. Allmyr, personal communication, February 17, 2021).

Network	Unit Name	Unit Type	Fuel	Q [MW_{th}]	Q [MW_{el}]	Efficiency
System CHP	Block 6	CHP	Municipal waste	133	48	1.03
	Block 7	CHP	Recovered Wood fuel	123	54	1.06
	Block 5	CHP	Branches	168	50	1.09

*Table 3: Technical data for existing heat generation technologies in system Mix. Based on Romanchenko et al. (Romanchenko D. , Odenberger, Göransson, & Johnsson, 2017). *: changed to biobased from fossil fuel.*

Network	Unit Name	Unit Type	Fuel	Q [MW_{th}]	Q [MW_{el}]	Efficiency /COP
System Mix	Renova	CHP	Municipal waste	130	43	1
	Preem		Waste heat	60	-	1
	ST1		Waste heat	85	-	1
	Säv CHP	CHP	Wood chips	110	13	1.11
	Rya CHP	CHP	Biogas*	295	245	0.91
	Högsbo CHP	CHP	Biogas*	14	13	0.79
	Rya HP 1-2	HP	Electricity	60	-	3.6
	Rya HP 3-4	HP	Electricity	100	-	3.15
	Rya HOB 1	HOB	Wood pellets	50	-	0.92
	Rya HOB 2	HOB	Wood pellets	50	-	0.92
	Säv HOB 1	HOB	Biogas*	90	-	1.01
	Säv HOB 2	HOB	Biogas*	60	-	0.90
	Ros HOB 4	HOB	Biogas*	140	-	0.97
	Ang HOB	HOB	Bio oil	105	-	0.90
	Rosenlund HOB1	HOB	Bio oil*	440	-	0.98

Table 4: Technical and economical for possible investment choices available in the model. The technical lifetime of the new investments are 25 years, except for New EB which has a technical lifetime of 20 years (The Danish Energy Agency, 2016).

Unit Name	Unit Type	Fuel	CAPEX [MSEK/MW$_{th}$, yr]	OPEX [SEK/MWh]	Power to heat ratio	Efficiency /COP
New HOB B	HOB	Wood chips	0.69	34	-	1.15
New HOB W	HOB	Municipal solid waste	1.47	82	-	1.06
New HOB BG	HOB	Biogas	0.062	10	-	1.04
New HOB BO	HOB	Bio oil	0.37	15	-	0.9
New EB	EB	Electricity	0.067	10	-	0.99
New HP	HP	Electricity	0.37	15	-	3.7
New CHP B	CHP	Wood chips	0.98	44	0.37	1.14
New CHP W	CHP	Municipal solid waste	2.44	244	0.302	1.04
New CHP BG	CHP	Biogas	1.70	42	1.15	0.94

Table 5: Assumed technical and economical for possible TES investment choices available in the model. Based on the Danish Energy Agency Catalogue (The Danish Energy Agency, 2016).

TES	Annualized cost [SEK/MWh, yr]	C-rate [h^{-1}]	Efficiency	Losses [%/day]
Large scale tank storage	2340	0.0166	0.98	0.2

For each system, a different heat demand profile is used. For System Mix, a demand profile consisting of data from the Gothenburg DH system from 2012 is used. For the other two systems the demand profiles are estimated based on simplified equations from (Sirén, 2016) with the assumption that the indoor temperature is constant (set to 20°C), and under steady-state conditions. The heat demand can be considered linearly dependent on the outside and indoor air temperature difference. From this temperature correlation and with the expected total demand of a normal year a heat demand is estimated. This is done by first calculating the temperature difference between inside and the outdoor temperature for each hour as according to equation 19, where *T(t)* is the outdoor temperature at hour *t* gathered from (SMHI, 2021).

$$\Delta T(t) = 20℃ - T(t), \forall t \in T(t) < 17℃ \;\; else \;\; \Delta T(t) = 3℃ \tag{19}$$

By limiting the temperature difference to not be lower than 3°C, the need for heating of water during warm periods is sufficiently captured. For system CHP the temperature data was collected from the closest active measuring station, namely Enköping MO. As the three reference systems are all geographically located in the southern part of Sweden, the temperature data for system HOB was collected from the measuring station Skellefteå airport to incorporate a Northern geographical location. The temperature difference and total annual demand is used to calculate the heating demand for every hour according to according to equation 20, where *D(t)* is the demand at hour t and D_{tot} the total annual demand.

$$D(t) = \Delta T(t) \frac{D_{tot}}{\sum_t \Delta T(t)} \tag{20}$$

These constructed demand profiles have a higher diurnal variation than the profile based on measurement data, but since the model will underestimate costs of part load and startup this is not expected to significantly impact the results

3.2 Deterministic Sensitivity Analysis

The deterministic sensitivity analysis uses the core model with a deterministic set-up, i.e. the electricity price, the hourly heat demand, fuel prices and techno-economical parameters of the available heat production units are assumed to be known ahead of the optimization and are provided exogenously to the core model.

In the deterministic model, the electricity price of 2019 is used. The electricity price is taken for the SE3 region from Nord pool SE3 region from Nord Pool (Nord Pool, 2021) and is shown in Figure 7.

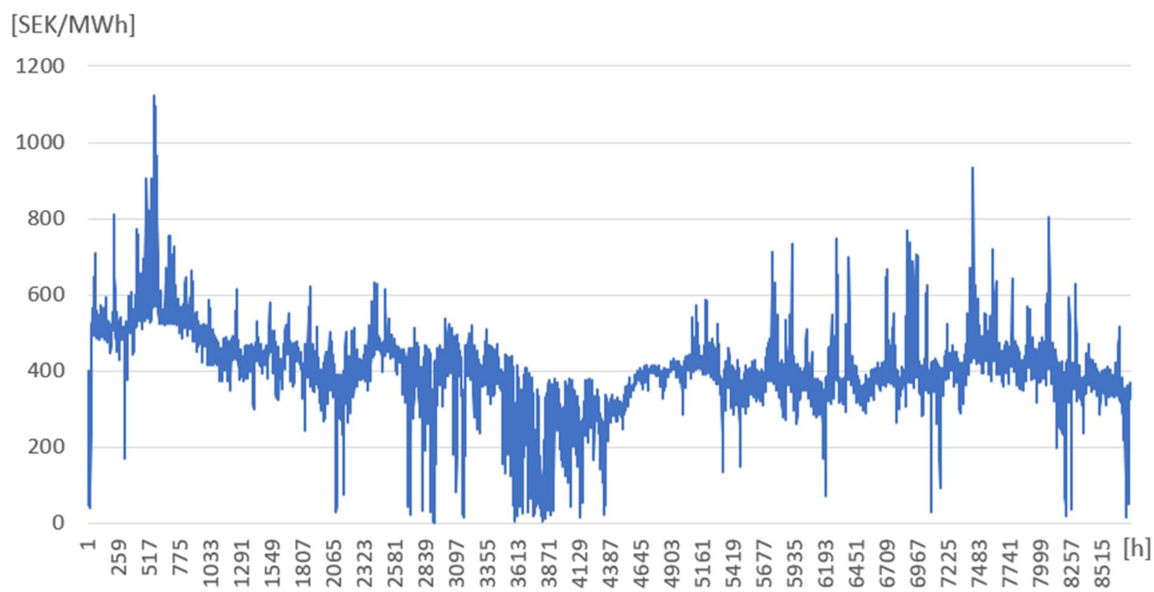

Figure 7: The electricity price in Sweden (SE3) 2019 that is used in the deterministic model. The mean price was 405 SEK/MWh this year.

The deterministic model is applied to the three DH systems in order to evaluate the sensitivity of investments, operations, and total system cost when the following cases are analyzed:

- *Base case:* Current (Year 2019) levels of biofuel prices, heat demand and the availability of industrial waste heat.
- *Cold winter*: The heat load is increased with 20% during hours 1-1500 and 7500-8760.
- *High biofuel cost:* The price of biofuels is increased according to Table 6.
- *No industry*: The availability of industrial waste heat is removed

Table 6: The assumed cost of biofuels used in the sensitivity analysis. The base price is used in all cases except the high biofuel cost case, where the higher price is used. The increased prices represent an estimation of future prices for 2030 according to *(Sandin, Sahlén Zetterberg, & Rydberg, 2019)*.

Type	Base price [SEK/MWh]	High price [SEK/MWh]
Wood chips	200	400
Bio oil	596	800

Biogas	480	770
Recovered wood fuel	90	90
Branches	198	400

3.3 Stochastic Uncertainty Analysis

The core model described in 3.1.1 is further developed by incorporating stochastic programming. An overview of the stochastic model set-up is visualized in Figure 8. The stochastic parameters in this model are the electricity price and the heat demand. Only these two are included as stochastic parameters since they are inherently stochastic, due to their weather dependency and annual variations described in Section 2.4, in contrast to e.g. the availability of industrial waste heat, for which changes are usually known ahead of time. In the stochastic model, the 1st stage variables are the investment decisions, since investment decisions must be made before the realization of the stochastic parameters, due to long construction times before actual commissioning. The 2nd stage variables are the operational decisions, since the operational decisions typically are made in near-time hour by hour when the stochastic parameters are better known. $P(s_i)$ denotes the probability of scenario s_i. As it is difficult to estimate which of the scenarios is more likely to occur, in this model all scenarios have equal probability and, thus, the probability is equal to one divided by the number of scenarios for each scenario.

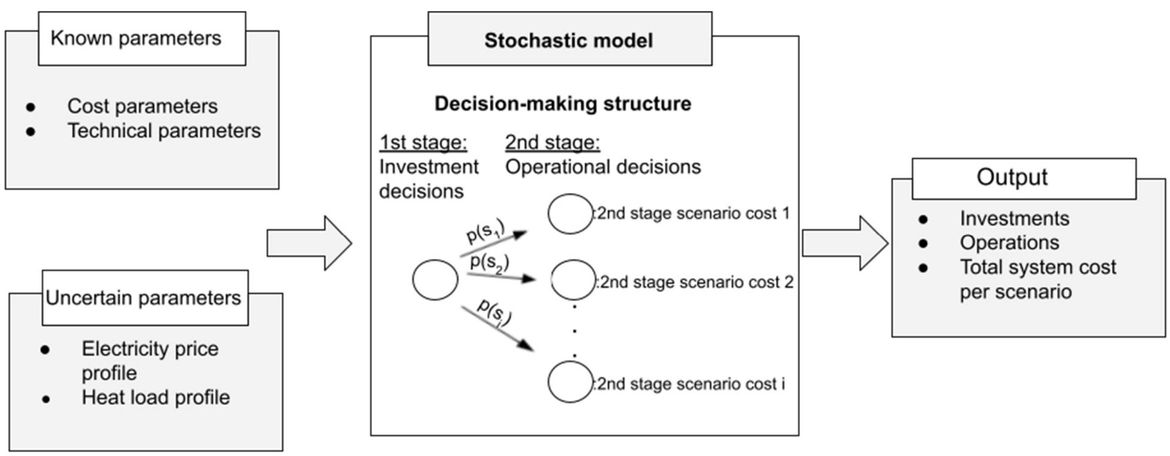

Figure 8: Overview of the stochastic model set-up. The input data consists of known parameters and uncertain parameters with a known probability. The model minimizes the expected cost of the two-stage problem and an output is received of what the optimal investments are as well as how the systems should operate in the different scenarios.

3.3.1 Stochastic Model Adaptation

In this section a general mathematical description of how the stochastic program works will be presented.

If s denotes a realization of the stochastic variables and $S = \{s_1, s_2 \ldots, s_i\}$ is the set of possible outcomes, the model adaptation for the stochastic program can be written:

$$\begin{aligned} & Min_I\, C_{tot} = C_{inv} I + \mathbb{E}[Y(I,s)] \\ \text{s.t.} \quad & I \geq 0 \\ \text{where} \quad & Y(I,s) = Min_Q\, y_s^T \\ \text{s.t.} \quad & h_s = T_s I + W_s Q(s), \quad Q(s) \geq 0, \ \forall s \in S. \end{aligned} \tag{19}$$

Here the first two lines define the first-stage problem and the third and fourth lines the second-stage problem. C_{tot} is the objective function to be minimized, I is the here-and-now decision variables of how large investments should be and C_{inv} the cost coefficient of the decision variables. $\mathbb{E}[Y(x,s)]$ is the expected value of the optimal solution to the second-stage problem. In the second stage, the stochastic variables are determined, and the objective is to minimize the variable cost during a year, while meeting the constraints defined in section 2.2. In the fourth row h_s are the constraints, T_s the transition matrix and W_s are the cost coefficients of the second stage decision variable $Q(s)$ which is the heat generation for each production unit for each scenario s.

3.3.2 Stochastic Scenarios

The stochastic DH system model is applied to systems HOB, CHP and Mix, respectively. Each system has the same existing units and investment options as in the deterministic model. What changes with the stochastic model compared to the deterministic one is that the heat load and electricity price profiles now are stochastic parameters instead of known parameters. The profiles consist of 8760 joint random variables (one for every hour) meaning that there is a probability for a profile and not a random electricity price at every hour.

For the electricity price there are five possible outcomes with different mean prices and variability. The first outcome is the same electricity price profile used in the deterministic model from Nord Pool 2019. The other four prices are constructed generic price profiles presented in Table 7. They are step functions that have a period of a week between having high or low electricity prices. There are two different average prices and for each average price there are also two different amplitudes of the step function to increase the variations of the electricity price. The electricity price is lower in the middle third of the year to show the seasonal variations. Together the four generic prices capture differences in how large and small variations, as well as higher and lower average prices affect the systems.

Table 7: The price levels used in the created electricity price profile. The period between high and low prices is a week. The annual average price is 600 SEK/MWh and 300 SEK/MWh for the high and low average respectively.

Electricity prices	*High avg - Low var*	*High avg - High var*	*Low avg - Low var*	*Low avg - High var*
Hours 1-2920 and 5841-8760	640±60	640±180	355±105	355±315
Hours 2921-5840	515±65	515±195	187.5±62.5	187.5±187.5

The heat load profile has 3 different outcomes. The first one representing a "normal" year for each DH system as in the base case in Section 3.2. For the other two profiles, hours 1-1500 and 7500-8760 are either 15% higher or 15% lower, representing a cold and a warm winter respectively. The demand is only changed during the winter hours of the year since the demand is less dependent on outdoor temperatures during the summer hours, when the use of hot water is a more significant share of the demand. Together, the 5 different electricity prices and the 3 different heat demands create 15 scenarios, which the stochastic model optimizes for.

3.3.3 Value Assessment of Uncertainty Analysis

To investigate the economic value of taking uncertainties into account when making investment decisions, the investments from the deterministic *base case* optimization are used as input for all the stochastic scenarios. This means that no further investments are allowed and only the dispatch of the units is optimized for all scenarios. Since the investments made in the *base case* of the sensitivity analysis do not take uncertainty into account and the stochastic optimization do, the two optimizations are compared to analyze the economic risk on total system cost associated with not including uncertainties in investment and operational decisions. The comparison is done by calculating the difference in total system cost for each scenario according to equation 21, where s denotes the specific scenario.

$$\Delta C_{tot}(s) = C_{tot,deterministic}(s) - C_{tot,stochasti}\ (s) \tag{21}$$

4 Results & Analysis

In this section the results of the models are presented and analyzed. First, the results from the deterministic sensitivity analysis are presented then the results of the stochastic optimization. The results are presented in terms of investments, dispatch and total system cost.

4.1 Investments in Deterministic Uncertainty Analysis

The investments made in the optimization of the deterministic model for each case and system are shown in Figure 9 as percentage of the peak demand of the *base case*. For all systems and cases there are investments made in TES. The reason that the TES technology is applied to such a great extent is that the TES is used to smoothen out the production and thus reduce the need for expensive peak generation units cost-effectively. When looking at the specific case *high biofuel cost,* the TES size increases for the all three systems compared to the *base* case. This is due to the marginal cost of heat increases when biofuels are on the margin, which leads to the TES becoming more valuable. For system CHP the TES size increases the most in the *cold winter* case. In this case there is a need for additional heat generation capacity and therefore the model also invests in a biogas HOB. By increasing the size of the TES, the full load hours and invested capacity of the new biogas HOB can be kept lower, but at this capacity for the TES it stops being cost-effective to make an even larger TES compared to the biogas HOB.

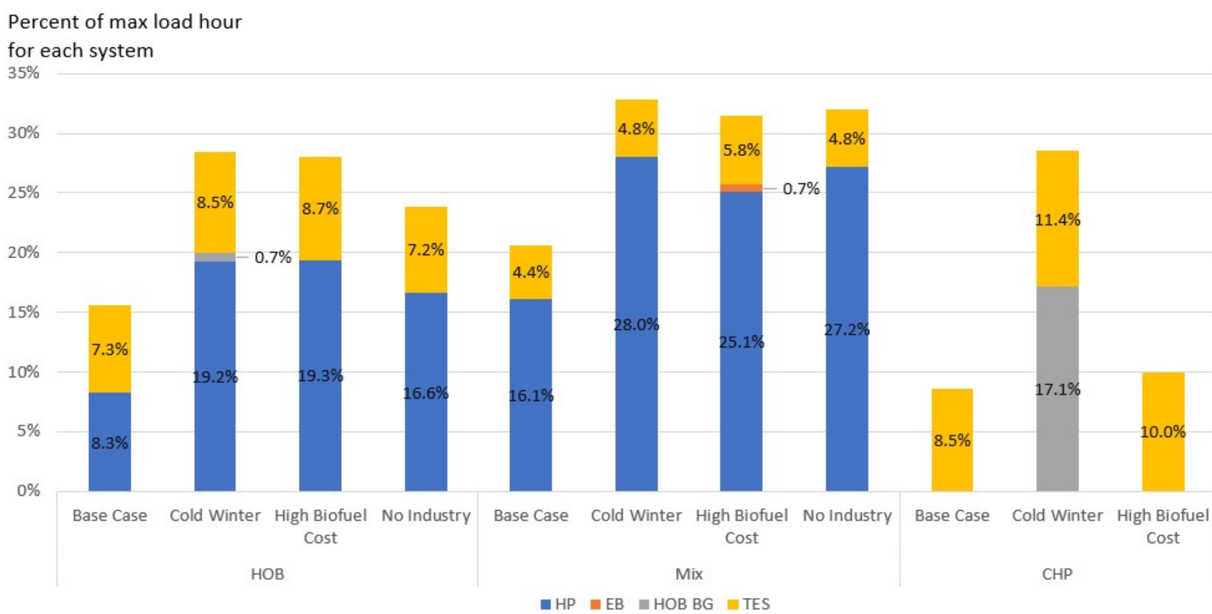

Figure 9: Investments made in the deterministic model for each case in the three systems. The values are presented as percent of the maximum load hour for the systems of 41, 1313, and 630 MW for systems HOB, Mix, and CHP respectively. For TES it is the output capacity that is shown which is linearly related to its size in energy [MWh] with a factor of 0.0166 as explained in Section 3.1.2.

In both the HOB and Mix systems, investments into new HPs are made in all cases. With the electricity prices of 2019, the HP with a COP of 3.7 has a relatively low operational cost with only the industrial waste heat and municipal waste CHPs or HOBs having a lower operational cost for most hours. This low operational cost is the driving factor for making the investments in HP, and since the HP also has a comparatively low investment cost, it is possible to invest in the HP even though there are other units available for production, in order to reduce the total cost of the heat generation. In the *cold winter* case, the investment in HP is increased in the HOB and Mix systems compared to the base case. This occurs since when the heat demand is increased in the *cold winter* case, a larger capacity of HP can be cost-effectively utilized. When removing the industrial waste heat from the HOB and Mix systems, it was replaced by investing more into larger HP capacity. In both systems, the HP capacity increased almost exactly as much as the size of the industrial waste heat capacity that was removed, meaning that in terms of capacity, the HPs cover the lost capacity as a base load unit. In the *high biofuel cost* case, a similar trend could be observed of increased investments in HPs, but in this case the HP is not replacing base load, instead it is replacing peak and mid load units together with the TES. These results regarding the HP investments show that HPs can be invested in both as a base load unit and to reduce the use of peaking units if they become too expensive.

There are some investments in peak units in the cases. For system HOB, a biogas HOB is invested in the *cold winte*r case. The biogas HOB is not necessary for its capacity to meet the demand during the cold year since there still exists spare capacity, but rather it is invested in since it has a lower variable cost than the existing bio oil units. During such a cold year, there are enough hours where peak capacity is needed for the biogas HOB investment to be beneficial. For system Mix in the *high biofuel cost* case an investment is made into an electric boiler. This is done to reduce the use of the now even more expensive biomass fueled peak units in the system to reduce the total system cost. For system CHP in the *cold year* case an investment was made into a biogas HOB. This investment is made since the system cannot otherwise meet the heat demand of the maximum load hours, but with the slightly larger TES and the biogas HOB the system can meet the demand for all hours. The two reasons for further peak generation investments are seemingly either to handle high load cases or to reduce costs of existing expensive peak generation. Which unit that is invested in to reduce the cost of expensive peak generation, depends on the ratio between the electricity and biogas price during the hours it is producing.

4.2 Dispatch in the Deterministic Study

The operations in the district heating system is linked to the investments made in the deterministic model and by the different cases. In Figure 10, the full load hours (FLH) for some units in system Mix can be seen for all four cases. The units excluded from the figure are peak units with very few FLH. Data of FLH for the units in the remaining systems can be found in the Appendix A.

In the *cold winter* case, many units are operated with a reduced number of FLH even though the demand is increased. The heat output is increased from the HP investment, but as the HP capacity is significantly increased in the cold winter case compared to the base case, the full load hours actually decreases. As the investment in the new HP is larger in the *cold winter* case than in the *base case*, the need for additional heat generation from the other HPs is decreased, and therefore the FLH of these units are decreased. This result is also seen in system HOB, where the FLH of the large wood chip HOB is reduced. In system HOB most of the additional energy needed in the cold winter comes from the increased HP investment. For systems HOB and Mix, a general increase can be seen in the utilization of peak units, but they are still few. For system CHP in the *cold winter* case, the base load units remain largely unaffected. A larger difference can be seen in the “peak” CHP plant, which increases its FLH from about 940 in the *base case* to 1700. The new biogas HOB is used only at very high demands and generates heat corresponding to 80 FLH.

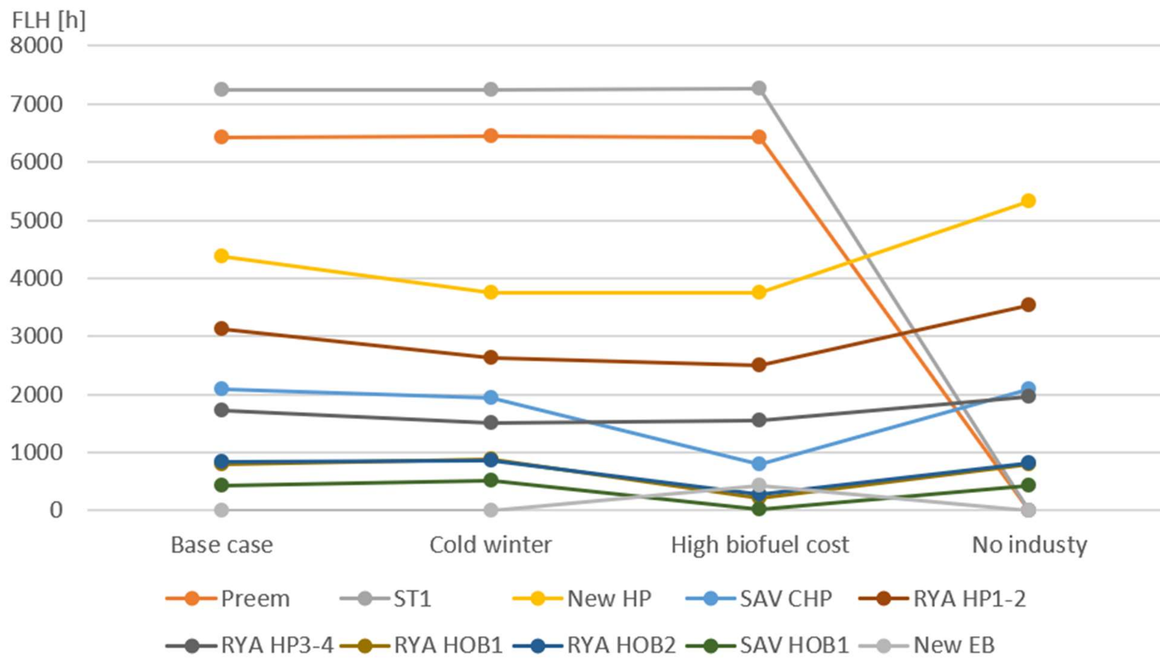

Figure 10: Full load hours of some units in system Mix for each case. Units not included in the figure are the ones with very few FLH. Note that the size of the new HP changes between cases so the energy produced is not linear to the amount of FLH. Also note that RYA HOB 1 and 2 follow each other since they have similar technical parameters.

In the no industry case, a prominent trend for systems with HP capacity is that the heat output from the HP units is increased. For system Mix, the investment in HP is larger compared to the *base case*, which allows the new HP to make up for almost all the lost waste heat from the industry. The only unit which is placed below the new HP in the merit order (i.e. has a lower operational cost), namely the waste-fired CHP Renova, is already producing at its rated capacity and can therefore not increase its production making the new HP the cheapest way of producing additional heat. In system HOB, however, the HP does not produce as much heat as the lost industrial waste energy. Instead the extra heat production required to meet the demand is shared between the waste HOB and the HP. They share this extra heat production since the waste HOB is lower in the merit order than the HP and therefore will produce more heat whenever it can. Since the waste HOB was already producing at its rated capacity during some parts of the year in the base case, the HP will produce more heat to cover for the lost industrial waste heat at those hours. No significant change in the other units in the systems was observed when removing industrial waste heat. This can be put in contrast to the *cold winter* case, where there were similar actions taken in order to adapt to the case, i.e. similar investments, but the operations of the other units in the system were affected more than in the *no industry* case.

A common trend in all cases for systems with capacity in both HP and biofueled units is that the merit order between these units change depending on the hourly electricity price, as the price ratio between electricity and biofuels changes. At hours with a high electricity price, the HP units can decrease their heat production in favor of an increasing heat production from bio fueled units and vice versa, since the operational cost of HPs is increased with an increasing electricity price. By changing the merit order between electricity fueled units and biofueled units, the total system cost can be kept down. In system HOB, the operational cost of the HP becomes larger than the wood chip HOB when the electricity price is over 775 SEK/MWh. This results in hours where the HP either reduces its production or shuts off, until the electricity price returns to lower values. For those hours, the TES is used to support the wood chip HOB to produce the lost heat from the HP. In system Mix the same behavior is observed, but for different values since another biofueled unit is competing, namely Säv CHP. Säv CHP also utilizes wood chips as fuel, but since the unit is a CHP it also generates revenues from electricity generation sales, thus, the operational cost of Säv CHP decreases with an increasing electricity price. The breakpoint in electricity price where Säv CHP becomes cheaper than the HPs in system Mix is between 440 SEK/MWh and 500 SEK/MWh for the HPs. The breakpoints are different for the HPs in system Mix since they have different COP and, thus, operational costs. The breakpoint of when the merit order is shifted occurs at different values for the two systems and even different values within the same system. This means that these shifts can vary considerably between different systems making them sensitive to different ratios between electricity and biofuel price.

In the high biofuel cost case, all systems adapt dispatch of units to reduce the use of biofuels. In system Mix the increased HP capacity is used together with the electrical boiler and TES investments to reduce the use of the bio fueled units such as the wood chip fired Säv CHP and many of the HOBs (especially the peak units) in order to reduce costs. The same results can be seen for system HOB, where peak generation (which uses bio oil) is almost completely removed and the use of the wood chip HOB is roughly halved. For system CHP the increased cost of biofuels decreases the use of the CHP unit Block 5, which is the only plant that has an increased operational cost. For Block 5 to reduce its heat production, heat needs to be produced somewhere else. In system CHP this extra production comes partially from increasing the TES size and using the other CHP plants for more hours during low-demand periods, but this measure is limited by the fact that the other two CHP units often already are producing to their maximum capacity. Instead the main source of extra heat production comes from increasing the heat output from the CHP units by refraining from electricity production to a greater extent than in the *base* case, i.e. using the R variable described in Section 3.1.2. This can be seen in Figure 11 where the sum of R divided by the sum of all electricity production in each scenario is shown for system Mix and system CHP. For system CHP there is a large increase in the use of the R variable in the *high biofuel cost* case compared to the other two cases, due to the increased operational cost for Block 5.

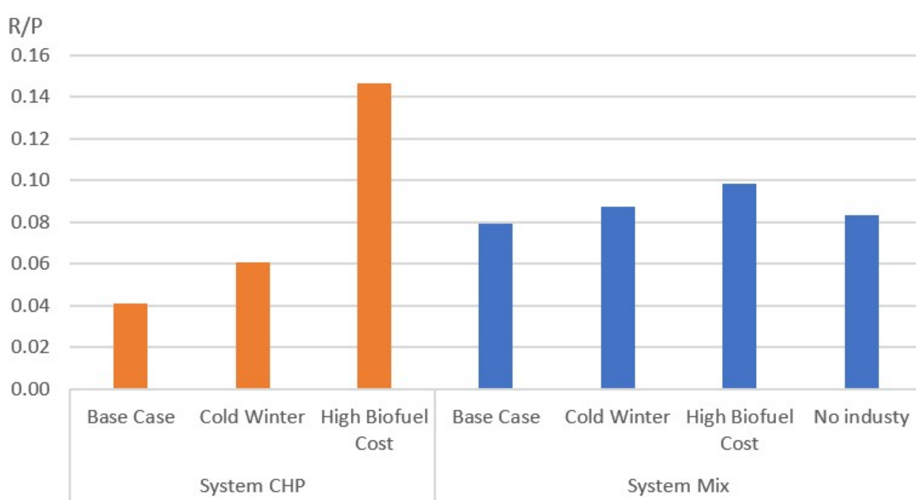

Figure 11: This figure shows the sum of R divided with the sum of P, i.e. extra heat produced from CHP plants by refraining from electricity production divided with the amount of electricity produced in each case. System HOB is not included since it does not have any CHP units.

In the two systems with CHP units, refraining from electricity generation in order to produce more heat is done in all cases. This flexibility measure is used at hours where the marginal cost of producing heat exceeds the marginal cost of electricity, and it becomes more economical to produce heat than electricity. During these hours the CHP units which refrain from electricity production can fulfill the role of a peak PtH unit, such as an electric boiler.

4.3 Impact on Total System Cost in Sensitivity Analysis

The total system cost for each case and system, normalized to each system's *base case*, is presented in Figure 12. For system CHP the total cost is negative due to electricity sales generating more income than the expenses, meaning there is an annual profit generated. The three systems show similar trends regarding the total system cost between cases. When industrial waste heat is removed, low-cost heat needs to be replaced either by increasing production from existing units or by making new investments. In system Mix the total system cost in the *no industry* case is increased nearly with a factor 2 compared to the base case, whereas in system HOB the *no industry* case is only changed with a factor of approximately 1.3. The share of industrial waste heat is larger in System Mix and therefore the change in total system cost is greater. Since low-cost heat needs to be replaced, the *no industry* case is the most expensive even though there are cases where more new investments are made. In system HOB for example, the *cold winter* case has the most investments made without being the most expensive case. This is since the investments in this case decrease the use of high variable cost units, unlike the no industry case. In the *cold winter* and *high biofuel cost* cases*,* all three systems follow the same trend. The systems show greater sensitivity to the increase in demand than the increase in biofuel costs. The reason for this trend is that in the *cold winter* case more heat needs to be produced and therefore the usage of peak units is increased, which affect the total system cost more than the increase in operational cost for the *high biofuel* case.

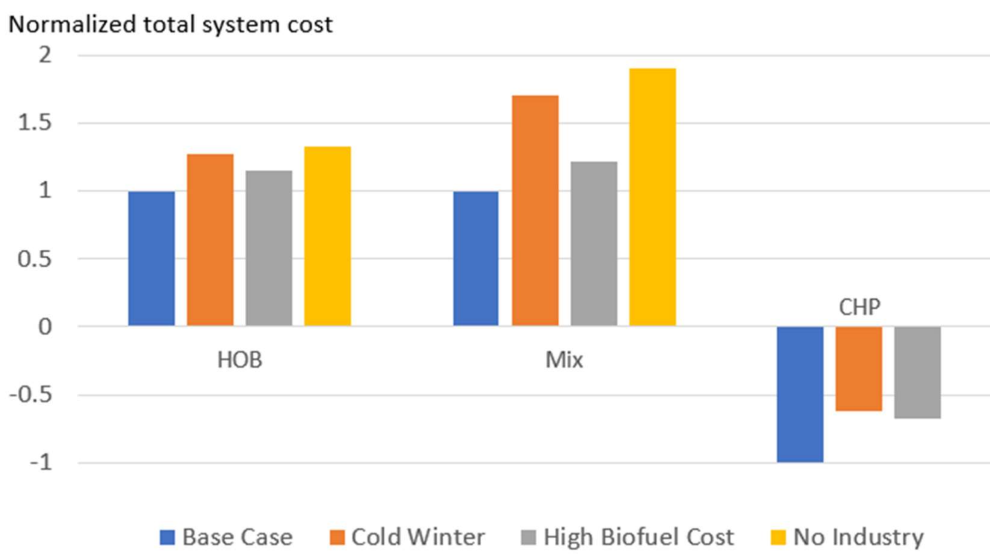

Figure 12: Total cost of the systems in each case. For system CHP the total cost is negative due to electricity sales generating more income than the expenses, i.e. there is an annual profit. A greater negative value indicates a higher annual profit. System CHP does not have a No industry case since the system does not have existing industrial waste heat.

4.4 Investments with Stochastic Uncertainty

The investments made in the optimization when the heat demand and electricity price was treated as stochastic parameters can be seen in Figure 13 together with the investments from the deterministic *base case*. In the stochastic optimization, the expected value of the total cost is minimized, meaning that the resulting investments are the ones that perform averagely best for the defined scenarios.

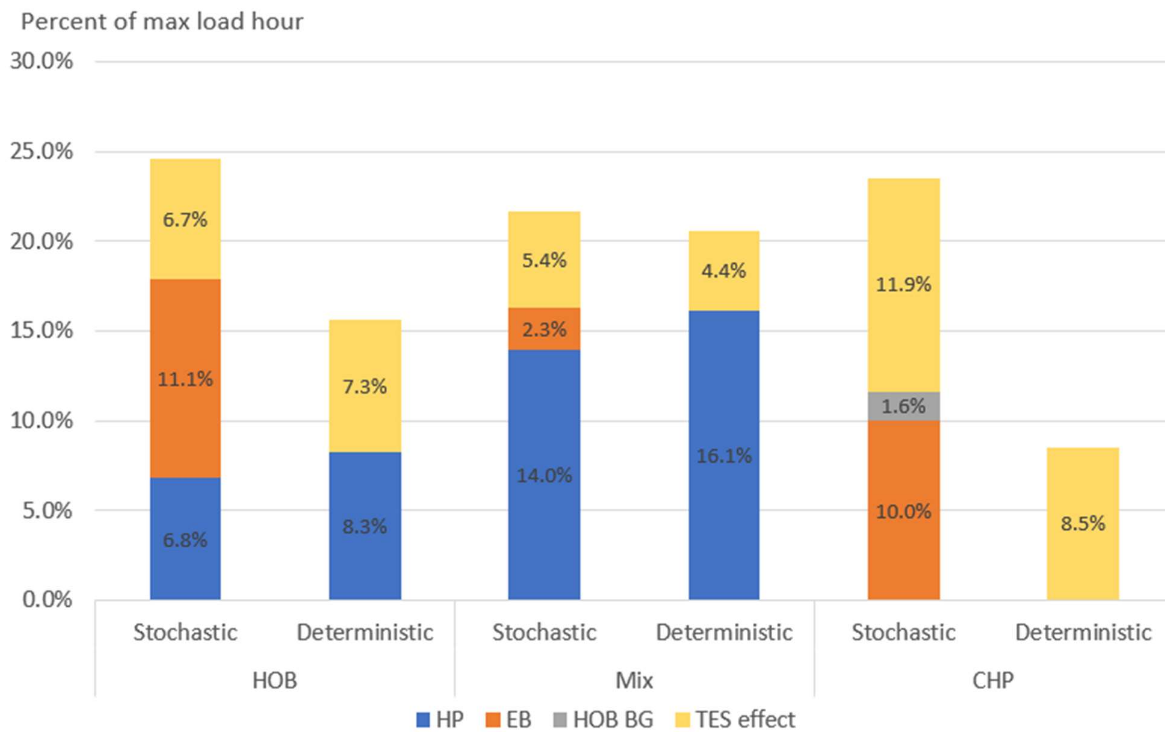

Figure 13: Investments made in the stochastic model and the deterministic model for each system presented as percent of the peak heat demand of the base case for the system. For TES, the output effect of the TES is used to show the investment size, which is linearly related to the size of the TES in MWh as described in Section 3.1.2.

For the systems, an increased amount of investments can be seen in capacity with low investment cost (i.e. electrical boiler and biogas HOB) and for systems HOB and Mix, a decreased amount of investments into HP. Factors decreasing the amount of HP invested in are low demand and high electricity prices, where the HP either produces less heat or for a higher price (i.e. HPs are less competitive). By investing in EB instead, the benefit of using power-to-heat technology in scenarios with low electricity price can still be capitalized on. In the scenarios with many hours of low electricity price the higher efficiency of a HP is not that beneficial when compared to a EB since the fuel cost becomes small relative to the investment cost. System Mix does not invest as much as system HOB in EB, and that is partially since the large waste CHP plant can refrain from electricity production at hours where selling electricity is not beneficial in order to produce heat. This measure is comparable to using EB, since electricity is traded for heat at about a one-to-one ratio.

CHP units refraining from electricity is also done in system CHP, but in system CHP investments need to be made in order to have enough capacity to meet the demand at peak hours for the scenarios with a higher demand during the winter hours. Since there is a need for additional capacity in system CHP, the stochastic model invests in two different peak units, a biogas HOB and an EB, as well as a larger TES which can complement the existing production depending on what is the most cost-efficient in each scenario.

Regarding the investments in TES there is a general trend that TES is always invested in, regardless of system and uncertainty analysis method. However, no general trend can be seen when comparing the results of the deterministic and the stochastic optimizations in terms of the sizing of the storage. The sizing of the TES is thus seemingly system dependent and scenario dependent. A possible explanation for the lack of common trends of TES investment between the systems is that there are different factors that decide the marginal value of the TES for each system. In system CHP, the reason for increasing the investment in TES could be due to that there is a need for additional capacity, which is partially achieved by investing in a larger TES. Another reason could be that the larger TES allows the system to sell more electricity from the CHPs instead of producing heat, which can increase the profit from the CHP plants. Increasing the TES size can also reduce the use of peak units which are more expensive than base load units. The reason for the decreased size of the TES in system HOB, could be the investment in an EB. The peak production in a system with an EB and bio oil HOB will always produce from the cheapest alternative, resulting in a peak production that is less expensive or as expensive as a system with only one option. Hence, the profit generated by the TES from reducing the use of peak units is reduced as an EB is introduced to the system. Why this trend is not seen in system Mix, could be because of that system Mix already could utilize CHP plants to refrain from electricity production, and this system therefore was not affected as much by the introduction of an EB. Since system Mix has a wide range of units, there are many factors, such as the ones described above for system HOB and CHP, that affect the sizing of the TES in the stochastic model and the balance between different benefits and costs. Thus, the TES is beneficial in all system contexts to some extent, although the exact use of the storage is system specific and related to the other types of units available.

4.5 Dispatch in the Stochastic Study

In the stochastic model, the operation of the DH systems differs between the scenarios that the stochastic optimization is based on. In Figure 14, the full load hours (FLH) of the units that change the most between the scenarios in system Mix are shown. When two units change in which one has more FLH, it means that they have swapped positions in the merit order of the system for most of the hours in that scenario. In the figure, the scenarios are ordered by their electricity price in descending order. For the same electricity price there are three different heat demand scenarios ordered from a low demand scenario to a high demand scenario. Data of FLH for all units and all systems can be found in Appendix B.

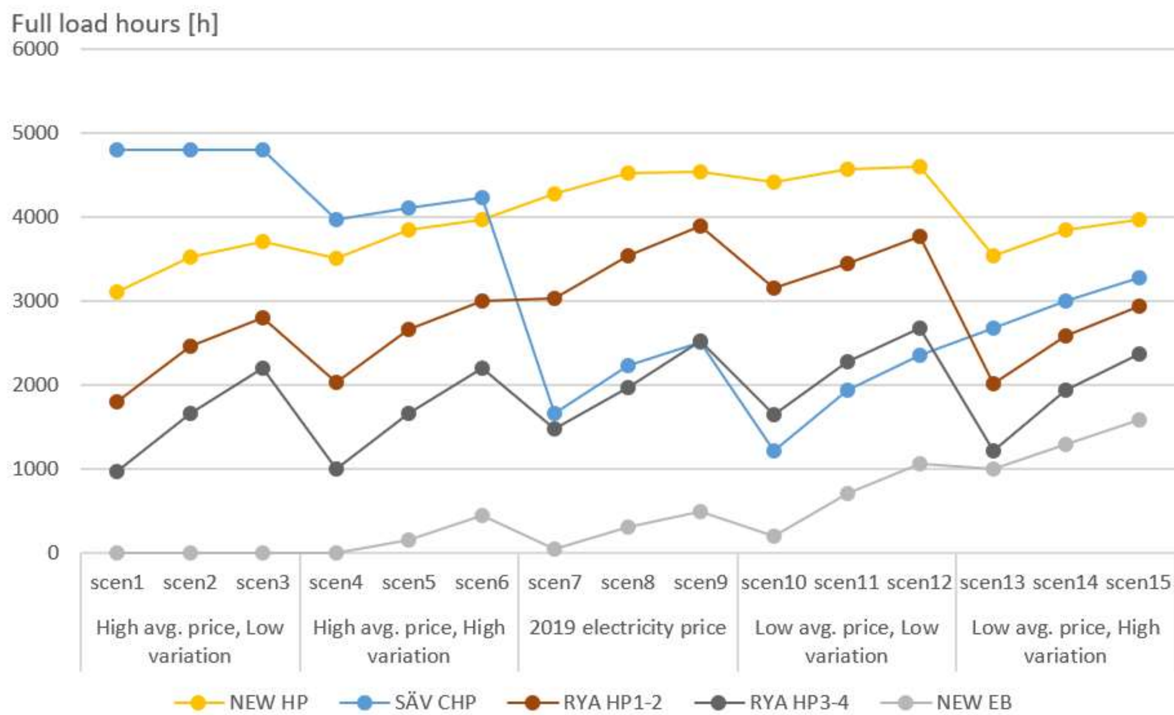

Figure 14: A plot of full load hours for a selection of the units in system Mix for each scenario from the stochastic model. The units shown are the ones most dependent on the electricity price variation in the system. Within an electricity price the scenarios are ordered from low demand to high demand.

In Figure 14 the wood chip fueled Säv CHP has a lot more FLH in the six scenarios with a high average electricity price than in the other scenarios, since a higher average electricity price is favorable for CHP operations. This is also seen for the CHPs in system CHP and is thus a general trend. The bio gas fueled CHPs in system Mix do not see the same increase in FLH for the scenarios with high electricity prices, they are instead more demand dependent and have more FLH in scenarios with high heat demand, acting as peak units since their operational costs are higher than the wood chip fueled CHPs. Säv CHP notably also has more FLH in scenarios 13-15, where the variation of the electricity price is high, than in scenarios 7-9 where the average price is higher. This is due to the high variation in electricity price in scenarios 13-15 resulting in more hours where the electricity price is high enough for the unit to be cost efficient, even though the average price is lower meaning that electricity price volatility matters for operating wood chip fueled CHPs.

The new investment in HP has more FLH in all scenarios compared to the two existing HPs in the system since the new HP has a higher COP. However, the three HPs in system Mix follows the same pattern regarding the FLH in each scenario. The FLH of all the HPs increases in scenarios 7-12 compared to scenario 1-6, since a lower average electricity price favors the production of HPs compared to CHPs as the running cost for HPs is decreased. In scenarios 13-15 the FLH of the HPs is decreased compared to scenarios 7-12. This is due to the high variations in the electricity price creating hours where the Säv HOB has a lower operational cost than the HPs, as described in the paragraph above. During half of the hours in the last three scenarios the electricity is significantly lower compared to all the other scenarios due to higher variations of the electricity price. This results in more FLH for the new EB since the running cost of this unit is decreased. In Figure 14 it can also be seen that all the PtH units are somewhat demand dependent, as the full load hours are increased with an increasing demand. The above-mentioned trends regarding the operations of the PtH units in system Mix can also be seen in the other two systems, it can therefore be a technology specific trend rather than system specific.

One operational parameter that undergoes significant change when the uncertain factors are considered is the R variable, which represents CHP units refraining from electricity use in favor of more heat production. The sum of R divided by the sum of all electricity production in each scenario is shown in Figure 15 for system Mix and system CHP, which have CHP units in their systems. In scenarios with a high average electricity price, electricity production is dominating, due to the large value of selling electricity. In scenarios with low average electricity prices however, a big shift occurs and up to half of the electricity that could be produced is instead sacrificed to produce heat. This is due to the marginal value of electricity at many hours is lower than the marginal cost of producing heat. The ability of a CHP to refrain from electricity production is thus a useful strategy in order to be cost efficient in multiple scenarios by either producing electricity or low-cost heat and the operations of CHP units are sensitive to the electricity price.

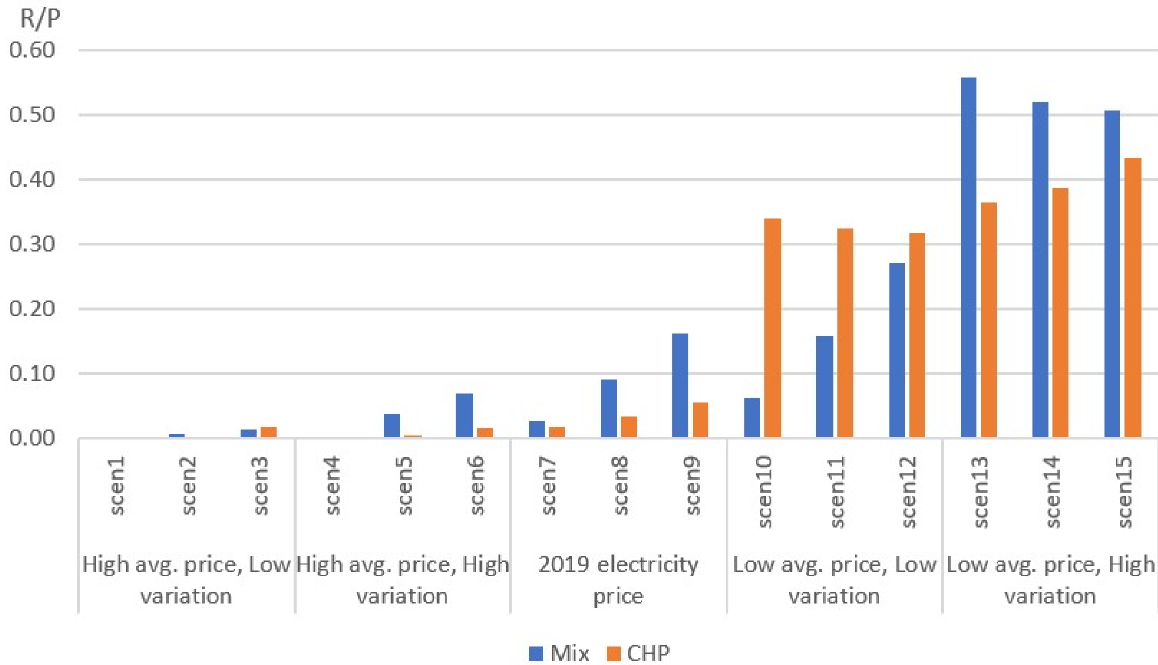

Figure 15: This figure shows R/P, i.e. extra heat produced from CHP plants by refraining from electricity production divided with the amount of electricity produced in each scenario. Within the same electricity price category, the heat demand goes from low to normal too high in the three respective sub-scenarios. In scenarios with low electricity prices, the model uses the flexibility of the R variable more since there is less value in producing electricity for a large portion of the year.

4.6 Value of Accounting for Uncertainty in DH System Planning

To evaluate the value of accounting for uncertainties in DH system planning, the investments made in the deterministic optimization of the *base case* are used as fixed investments for all the 15 scenarios that the stochastic model is optimized for. The resulting differences in total system cost per scenario for system HOB and system Mix can be seen in Figure 16. A positive value indicates that the deterministic optimization generates lower total system cost in the individual scenario and a negative value indicates that the stochastic optimization generates a lower total system cost. The blue dot marks the average difference between the models. In Appendix C data of total cost for each scenario can be found.

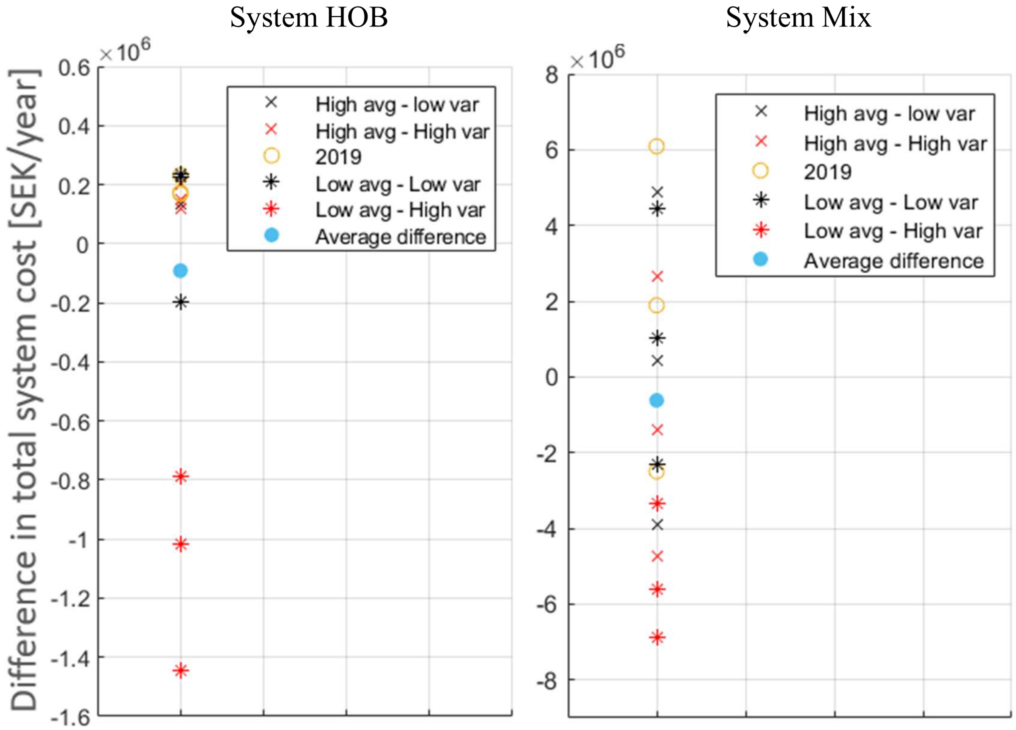

Figure 16: The difference in the total system cost between the investments from the stochastic optimization and the deterministic optimization for each scenario. Positive values indicate that the deterministic scenario is less expensive and vice versa. For perspective, the total system cost in the deterministic base case for system HOB is 1.3e7 SEK/year and for system Mix 1.9e8 SEK/year.

For system HOB, in 4 out of 15 scenarios the optimal investment from the stochastic solution is less expensive compared to the deterministic. The stochastic solution for this system is less expensive in the scenarios where the electricity price has a low average value and high variation, regardless of the demand. This is mainly due to the electric boiler from the stochastic optimization which is being used effectively in these cases with many hours of low-cost electricity. The investments from the stochastic optimization for System HOB is also less expensive in the scenario where the electricity price has a low average value and low variation with a high demand. In this scenario the EB also has advantages, as more peak units are required with the high demand and with the low average electricity price, the EB is a good option. For the remaining cases the stochastic optimization generates total costs higher than the deterministic base case. One contribution to this comes from that the total annualized investment cost is higher in the stochastic optimization, but only 46 000 SEK/year, which is not as much as the difference. The larger difference in total system cost comes from having increased operational costs by having a smaller HP and a smaller TES.

For system Mix, there are 8 out of the 15 scenarios where the investments from the stochastic optimization costs less than the deterministic optimization. In comparison with System HOB, the scenarios where stochastic optimization is less expensive than the deterministic one is more evenly spread out between the scenarios. For every scenario with low heat demand, the solution from the stochastic optimization is less expensive. This is since the total annualized cost of investments is 6.7 million SEK/year lower for the stochastically optimized investments, and the additional HP capacity from the deterministic optimization is not useful enough in these scenarios to make up for the investment cost. Further, the stochastic optimization is less expensive in the scenarios where the electricity price has a low average value and high variation, for similar reasons as for system HOB described above, but to a lesser relative extent due to the relatively smaller EB.

Even though there are several scenarios where the investments from the deterministic *base case* generates lower total system cost for the stochastic scenarios, the average total system cost for all the scenarios is lower for the stochastic solution for the Mix and HOB systems. This is to be expected since the purpose of the stochastic optimization is to minimize the expected value of the total system cost, which is the average total system cost since all stochastic variables have the same probability.

For system CHP, the fixed investment from the deterministic optimization proved infeasible for the scenarios with high demand. This is because the optimal investment for the deterministic *base case* cannot fulfill the requirement of meeting the heat demand for all hours in the scenarios with higher heat demand. This happens since the deterministic optimization is done for only one heat demand which does not have as high peaks as the high demand scenarios from the stochastic model, and it is in the deterministic model not optimal to invest in reserve capacity for the system since there is no current constraint or incentive to do so.

5 Discussion

In this analysis, the effect that different uncertainties have on DH systems are investigated. The analysis is not intended to be a predictive study on how DH systems should be designed, but rather to understand the effects and importance of uncertainty analysis for district heating system planning. If the intention is to make a predictive model of how district heating systems should be constructed, more detailed input data is needed in terms of the uncertain parameters and importantly also their probability distribution. In the stochastic optimization, generic electricity prices have been used, which does not give an accurate picture of future electricity prices, but they do give a good indication on how the DH systems are affected by possible changes in average price and variability.

In terms of evaluating the different optimization approaches to handle uncertainties, deterministic sensitivity is a time-efficient method to investigate changes in individual parameters. Each optimization took approximately 10 minutes, but as there is manual work for every parameter change and the model must be run several times (one time for each case) and the total computer time can be considered longer. The stochastic optimization model requires significantly longer computational time, e.g. one of the stochastic optimizations took approximately 5 hours to run. However, as each system is only optimized one time, it requires less manual work when the model is fully developed. As the stochastic approach required more computational time, it also required more computer capacity and therefore it was quickly realized that the stochastic approach was not laptop friendly. As both optimization approaches are linear, the development can be considered quite straightforward if the developer is somewhat familiar with using GAMS for energy system modeling purposes.

5.1 Dispatch and Investments

A prominent trend from the results is that all systems invest in a TES, regardless of case or scenario. In the sensitivity analysis it was observed that the investment size of the TES was increased with increasing biofuel prices. This is due to the marginal cost of heat increase more for peak units than base load units in the analyzed systems, which leads to the TES becoming more valuable. A conclusion from this is that if the difference in marginal price of heat between base and peak load units were to increase, more TES could be introduced. It is also observed from the stochastic optimization that investments in TES have a system and scenario dependency, as there are no apparent common trends in the stochastic optimization. A possible explanation for the lack of common trends of TES investment between the systems in the stochastic optimization is that there are different factors deciding the marginal value of the TES for each system. It is therefore important to account for uncertainties when it comes to the optimal size of TES investments, to understand underlying factors which determine the value of the TES for an individual DH system. However, it should be noted that the utilization of TES could be enhanced further if the variety of the TES technologies was more thoroughly investigated for each system. In this thesis only one type of TES technology is included, namely a large-scale tank storage. A greater variety of TES options could allow the model to choose the cost-optimal c-rate and add seasonal storage to a greater extent, creating a further optimized TES strategy.

A common trend for the systems is investment in PtH technologies, which mainly takes place as investment in HPs for the deterministic optimization and HPs in combination with EB in the stochastic optimization. As there are investments in PtH for most of the uncertainties applied, it is a useful technology for DH systems to adapt to future uncertainties. By having capacity in both PtH and biomass-based units, the systems can choose the less expensive production option at a specific hour and electricity price. This gives the systems more flexibility in their operations that can assure cost-efficiency when the cost of biofuels and electricity is changing. A system including biofueled and PtH units, is what in this work is defined as a Mix system. With the investments made in the sensitivity analysis and the stochastic optimization, we can see that system HOB is becoming more of a mixed system instead of a pure biomass HOB system that it was initially.

When investing in PtH technologies, possible limitations that has not been considered are the effect on the local power balance and for HPs the availability of a sufficient heat source. The heat source of the HP needs to be at sufficient temperatures and have enough energy for the HP to be efficient. A lack of a good heat source would lead to decreasing efficiency and thus less investments in HP for the systems. If the local electricity grid has issues with supplying enough electric capacity and energy, an investment in PtH technologies might not be possible even if it would otherwise be profitable. If new power cables are required for PtH to be expanded, the investment cost would increase, and this might affect the profitability of the PtH. On the other hand, it has been observed that the HPs and EBs stop or reduce their production and electricity use if the electricity price is high. This means that if the electricity price manages to signal issues in the electricity grid, the HPs will use less electricity and help the electricity grid during strained hours. However, the heat demand must be met regardless of electricity price. If high load hours coincide with high electricity prices, the PtH units might not be able to refrain from producing even if they are very expensive to run if there is no other spare capacity.

Another aspect regarding the local power balance is the effect that CHP units refraining from electricity production has. There is a risk that the hours with high heat demand coincides with hours where the power market is strained. Hence, the future possibility to refrain from electricity production without restrictions might not be an option in order to sustain the local power balance. If there were to be restrictions regarding refraining from electricity production, it would probably have a direct effect on the investment strategies in systems which rely on that flexibility measure. In the stochastic optimization it was observed that CHPs refraining from electricity production is sensitive to the electricity price, as the scenarios with higher prices have much more electricity production than the cases with low prices and that the variations of the electricity prices had an effect on the electricity production. This means that if the electricity price successfully manages to signal issues in the local power balance, CHP units should act to help the balance by producing electricity.

5.2 Value of Accounting for Uncertainty

When looking at the difference in total system cost between the stochastic and the deterministic optimization, it is observed that the difference in total system cost can vary considerably within a system and between systems. In system HOB there is a significant difference in the investments made in the deterministic *base case* and the stochastic optimization. This shows that the uncertainty of demand and electricity price of the stochastic model affected the system a lot and thus, the system is sensitive to the uncertainties, not only in the size of investment, but also in what technology that was invested in. The difference in the investments from the two optimizations approaches leads to differences in the total system cost in the scenarios, that in some scenarios are large (up 11% of total cost). This shows that system HOB is sensitive to the uncertainties applied in the stochastic model. By not taking the uncertainties into consideration, i.e. only using the investments of the deterministic optimization, great opportunities to lower the total system cost can be missed out on even if the deterministic optimization is a good option in many of the possible scenarios.

For system CHP, the investments from the deterministic optimization proved infeasible for the scenarios with high demand from the stochastic model, since there is insufficient capacity in system CHP. This shows the importance of taking high load cases into consideration, so that the risk of not being able to meet the demand can be minimized, since not being able to meet the demand can be very economically damaging in terms of reputation and loss of customers. This could for example be done by including an additional constraint in the model that assures that sufficient capacity exists in the system to always meet the demand or by including scenarios with the highest possible (within reasonable probability) heat demand in a stochastic model. Such an extreme demand should have a low probability so that the model does not overreact to the unlikely scenario. In reality, however, most systems have some reserve capacity and often in the form of fossil oil fueled HOBs, in contrast to system CHP which initially does not have any reserve capacity. In the *cold winter* case for the deterministic model, peak capacity was invested in the form of biogas HOB. In the stochastic study peak capacity was invested in the form of small amounts of biogas HOB, but mainly EB. The difference between which option is the most economical in the two models is the electricity price.

In this work, the use of electricity in DH is assumed to not impact the price of electricity, but especially with an increased amount of PtH units, this assumption could become less valid. It could be that electricity prices are more likely to be high at hours when the heat demand is larger (due to electricity being used for heat) which then could incentivize not having EB as reserve capacity. Similar problems concern the operations of CHP units, since the option to refrain from electricity production in favor of additional heat production can occur at hours where both heat demand and electricity prices are high. In order to fully understand and find the optimal solution to the electricity and DH system dynamics, both systems need to be modeled simultaneously, but it is clear that the DH system is sensitive to the electricity price when the demand of heat is high.

For system Mix, the investments from the deterministic *base case* and the stochastic optimization are relatively similar. This shows that the combination of technologies in system Mix already give the system the ability to adapt to the uncertainties applied in the stochastic optimization. The adaptation can be seen both in how the full load hours change between the scenarios and in how electricity production from CHP units change. The small differences in investments is why the difference in total cost in Figure 16 is relatively small and evenly distributed. Hence, in system Mix the economic risk is not as large and the importance of uncertainty analysis is smaller compared to the other systems. This means that stochastic optimization is less important for system Mix, but this is of course difficult to know before doing the stochastic optimization.

5.3 Recommendations for Future Work

For future work, it would be interesting to see what the results of a more predictive study of DH systems would be if it were to be made, i.e. to use predictions of the uncertain parameters, and possibly apply some other probability distribution instead of the more generic inputs used in this thesis. Further a continued development of the stochastic program into a multi-stage program instead of only two-stage program would be interesting. This way, development could be tracked over time to find out more about when investments should be made. A multi-stage program would also have the possibility to model units being decommissioned which could be useful for DH system owners.

In cities where the availability of electricity capacity is a limiting factor, it is likely a good idea to analyze the impact of this in modeling, since the optimizations from this thesis suggests that PtH units should be invested in.

6 Conclusions

This thesis investigates the importance of uncertainty analysis in district heating system planning by evaluating the sensitivity of operational patterns, investment choices and total system cost of Swedish DH systems to uncertainty in biofuel costs, electricity price, availability of industrial waste heat and the heat demand of the system. The uncertainty analysis was conducted on three DH systems with two optimization approaches, a deterministic sensitivity analysis and a stochastic program, which minimizes the total system cost by optimizing the investments and dispatch of units.

The study shows that when uncertainty in parameters is considered, the optimal investments may differ both in technology type and size. Based on the results, a conclusion can be drawn that technologies with low investment cost, mainly electric boilers, are favored to a greater extent when uncertainties are considered. Large heat pump investments were made for two of the three systems. The heat pumps decreased slightly in size in the stochastic optimization where uncertainties are considered, in favor of said electric boilers. Furthermore, important investments in thermal energy storage are a prominent trend throughout this study. The sizing of the storage capacity is sensitive to the uncertain parameters, resulting in different capacities depending on how the difference in operational cost between base and peak load is affected by the uncertainties. The resulting investments of the stochastic optimizations give all the systems the ability to use both electricity and biofuels to produce district heat, and a thermal energy storage that can shift the production in time.

In terms of sensitivity in operational patterns, outcomes of uncertain parameters may change the existing merit order between power-to-heat and biofueled units. The district heating systems can in that way adapt to be cost efficient in many future outcomes. The electricity production from CHP units varies depending on the electricity price outcomes in the stochastic optimization. At high electricity price CHP units maximize their electricity production and at low electricity prices they refrain from up to 50% of the electricity production, in favor of producing additional heat.

In terms of sensitivity of total system cost, the uncertainty analysis gives different results for each district heating system. Hence, the systems are sensitive to uncertainties to varying extents. A risk has been identified that potential economic benefits can be missed out on if uncertainties are not considered, either by not meeting the demand due to lack of capacity or by not being able to capitalize on low electricity prices. The system with a greater mix of production technologies was less sensitive in terms of investments and total system cost, to the uncertain parameters.

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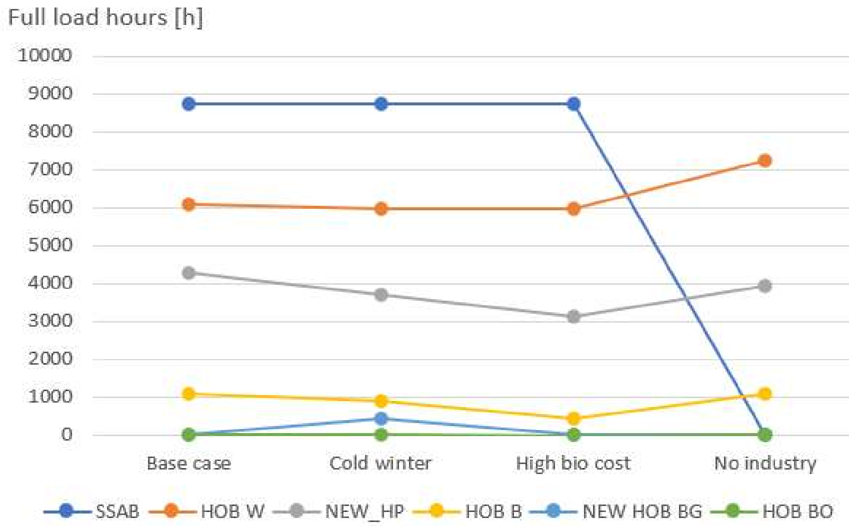
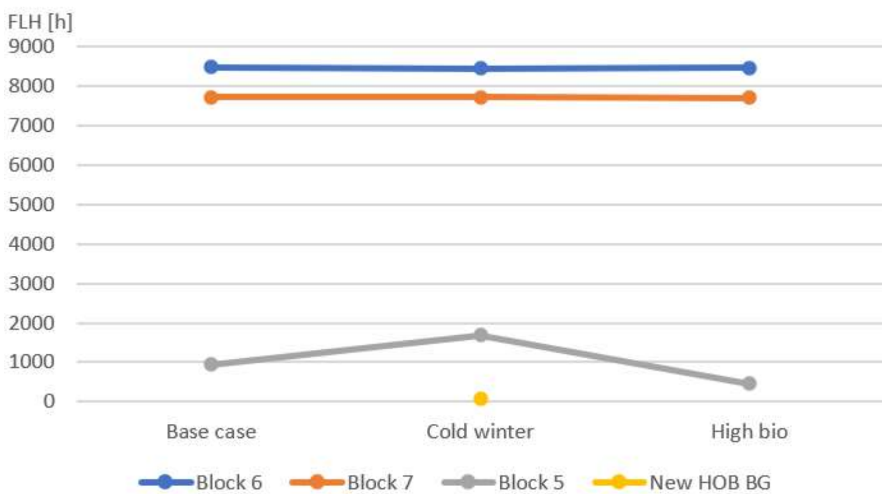
Appendix

A. Full load hours from deterministic optimization

Full load hours of the units in system HOB in the cases from the deterministic optimization.

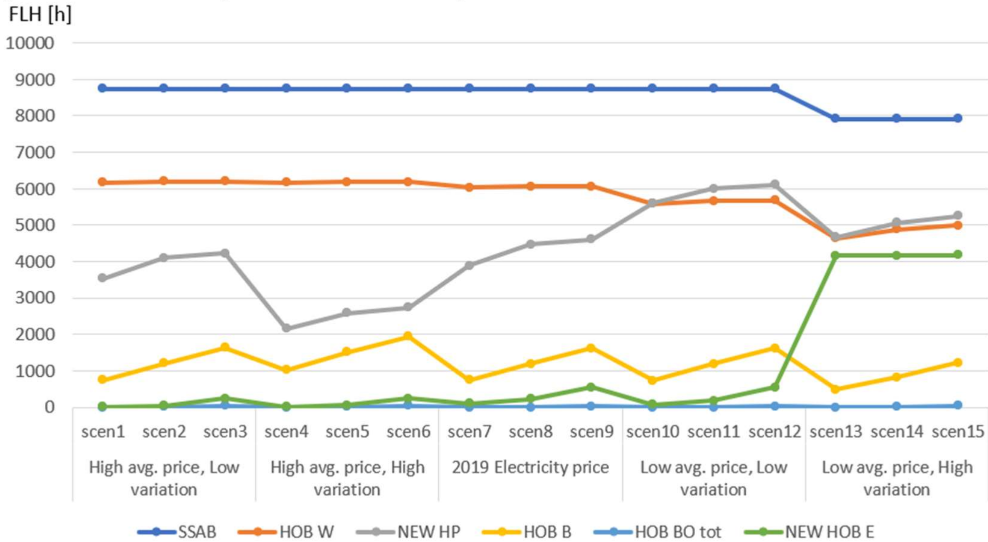


Full load hours of the units in system CHP in the cases from the deterministic optimization.

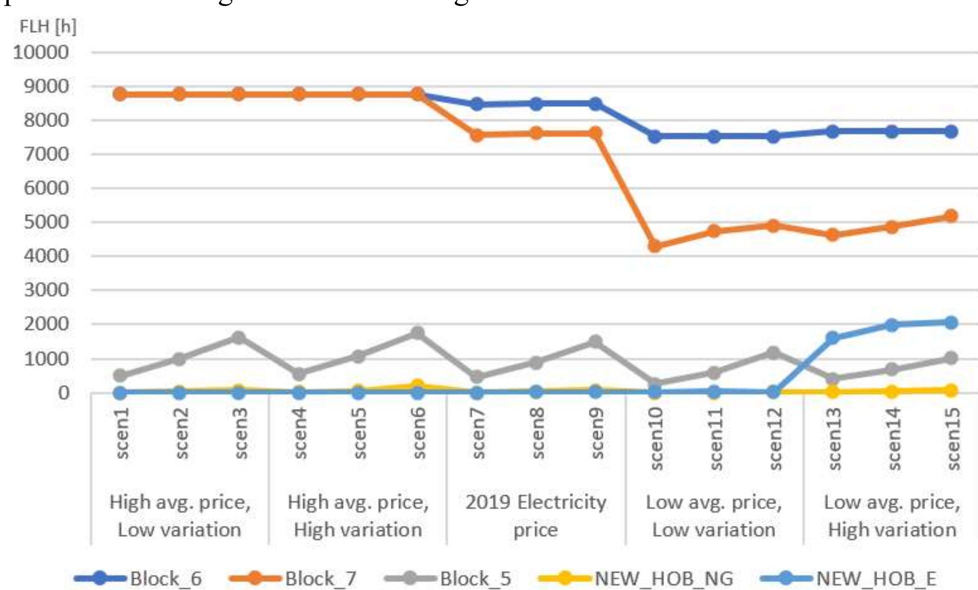


B. Full load hours by scenario from stochastic optimization

FLH in system HOB in each of the scenarios from the stochastic optimization. Within an electricity price the demand goes from low to high in the three scenarios.



FLH in system HOB in each of the scenarios from the stochastic optimization. Within an electricity price the demand goes from low to high in the three scenarios.



C. Total system cost

Table of the total system cost in each scenario from the stochastic model. The cost is normalized to the deterministic optimization of the *base case.* The fixed investments are fixed from the deterministic optimization while the stochastic is the investments from the stochastic optimization.

	Electricity price	2019			High avgerage - Low variation			High average - High variation			Low average - Low variation			Low average - High variation			
	Heat demand	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High	Average
Mix	Fixed inv	0.55	1.00	1.58	0.26	0.74	1.34	0.22	0.68	1.25	0.64	1.05	1.61	0.49	0.89	1.42	0.92
	Stochastic	0.54	1.01	1.61	0.24	0.75	1.37	0.20	0.67	1.26	0.63	1.06	1.63	0.46	0.86	1.40	0.91
HOB	Fixed inv	0.85	1.00	1.23	0.89	1.06	1.29	0.88	1.05	1.28	0.81	0.96	1.19	0.78	0.94	1.17	1.03
	Stochastic:	0.86	1.02	1.24	0.90	1.07	1.31	0.90	1.06	1.29	0.83	0.98	1.18	0.72	0.86	1.06	1.02
CHP	Fixed inv	-1.11	-1.00	N/A	-3.09	-3.01	N/A	-3.12	-3.04	N/A	-0.31	-0.19	N/A	-1.12	-1.00	N/A	-1.91
	Stochastic:	-1.03	-0.93	-0.73	-3.02	-2.95	-2.80	-3.04	-2.97	-2.82	-0.24	-0.12	0.07	-1.09	-0.99	-0.84	-1.57

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