Dealing with uncertainties in the operational planning of district heating plants

Master thesis

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Sustainable Energy Planning and Management

Aalborg University - June 2021

AALBORG UNIVERSITET
STUDENTERRAPPORT

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Title:

Dealing with uncertainties in the operational planning of district heating plants

Project:

Master thesis

Project period:

1st of February - 4th of June 2021

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Supervisor:

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Pages:

65

Submission date:

4th of June 2021

Summary

This report investigates how a Danish district heating plant should calculate the optimal bids in multiple deregulated electricity markets with marginal pricing auctions while assuming the district heating plant to be a price-taker. This research is crucial in the context of a transition to a 100% renewable energy system, as sector coupling between the electricity and district heating sector is regarded as a cost-efficient way to integrate large shares of fluctuating renewable energy in the Danish energy system. One of the barriers for succesfully coupling these sectors is the lack of bidding methods able to handle large uncertainties in the operational planning. Assens District Heating is selected as an instrumental case and four different bidding methods are compared: price-independent bidding, a single bid method derived from the price-independent bidding method but with an upper limit on the bidding price, the state-of-the-art heat unit replacement bidding method currently used in the operational planning tool, energyTRADE, and at last a method based on scenario generation and Sample Average Approximation techniques. Sample Average Approximation is a way to deal with stochastic optimization problems by finding the optimal decision across a number of likely scenarios instead. Forecasts and scenarios are generated using Monte Carlo simulation and a Markov Chain by training multiple transition matrices on historical data for aggregated solar irradiation, ambient temperatures, wind speeds and spot prices in Nord Pool Spot. Regulating prices are generated using Monte Carlo simulation and regresssion on historical data. The methods are modelled as a multi-stage mixed-integer linear program with a 5 days rolling planning horizon. The model constitutes a realistic bidding framework that simulates the real operation and bidding in sequential electricity markets under uncertainty. The results show that the method based on Sample Average Approximation is able to calculate bids that lead to both techno-economic optimal operation of the district heating plant, but also an operation that provides better sector coupling between the electricity and district heating sector, as electricity is purchased and sold according to price signals from the electricity markets. The results also show that participating in multiple electricity markets can lower the operational expenses of the district heating plant significantly, and that suboptimal bids made in the day-ahead market can be made up for by placing bids in the regulating market afterwards.

Acknowledgements

This project has been made in close collaboration with EMD International following my internship in the autumn of 2020. I would like to express my deepest gratitude to all the people at EMD International who have influenced my project in one way or another.

I am especially thankful for being introduced to this extremely interesting topic by my supervisor, Anders N. Andersen. This project would not have been possible without the guidance and resources that you provided me with.

Marta Irena Murkowska, I am grateful for your help and the ongoing discussions we have had during this project.

Lasse Svenningsen, thank you for taking your time to discuss the complexities of modelling time series forecasting.

Marc Roar Hintze & Dennis Dolleris, thank you for allowing me to use Assens District Heating as a case study and thank you for showing me around the plant for some hands-on experience on what is being modelled.

Contents

Chapter 1

Introduction

1.1 Towards a 100% renewable energy system

To mitigate the consequences of human-induced climate change, Denmark is committed to become carbon-neutral by 2050, which entails a net-zero emission of greenhouse gasses [1]. The biggest source of greenhouse gas emissions is the use of fossil fuels in the consumption of energy, causing 60% of the Danish emissions [2]. It is therefore necessary to replace the use of fossil fuels with renewable alternatives such as wind power, solar power, and biomass, which on the contrary to fossil fuels are replenishable sources of energy with significantly lower emissions of greenhouse gasses [3]. A large amount of renewable energy has already been integrated into the Danish energy system. From 2000 to 2019 the share of renewable energy in the final energy consumption increased from 10% to 35%, with biomass and wind power being the two main contributors [2]. Biomass is typically used for CHP production, which accounts for 18% of the Danish electricity production [2]. However, it is controversial whether the use of biomass is truly a low-emission source of energy [4], and at the same time biomass is a limited resource [5, 6]. It is therefore expected that a future 100% renewable energy system in Denmark will be based on mainly wind power and solar power [7], as a combination of these is the most cost-competitive alternative to fossil fuels [8]. While wind power and solar power are low-emission sources of energy, they introduce a new challenge to the energy system. Fossil fuels are a convenient source of energy, as they have a high energy density, can be stored easily, and dispatched at need. Wind power and solar power on the other hand are fluctuating and non-dispatchable sources of energy, which are subject to changing and uncertain weather conditions. Since electricity must be consumed and produced at once, and because electricity is extremely expensive and inefficient to store [9], flexibility in the surrounding energy system is necessary to accommodate large shares of fluctuating renewable energy [10]. Due to the amount of flexibility required and the timeline it is needed for, demand response in the traditional energy consumption will have a negligible effect on the ability to integrate renewable energy [10]. Solutions to increasing the flexibility of the system instead focus on inter-regional and cross-sectoral integration.

Inter-regional integration takes advantage of the difference in the fluctuations of renewable energy, as well as the difference in available renewable energy sources, between distant geographical areas [8]. Norway, as an example, has unlike Denmark access to a large source of renewable hydro power, which is subject to very different fluctuations than wind power, being the dominant resource in Denmark. Inter-regional grid connections exploit this to allow a more efficient and flexible use of the renewable energy sources, by exporting excess renewable electricity production to regions with deficit renewable electricity production. Denmark is already rapidly expanding the transmission capacity to the neighboring countries. Between 2021 to 2023 this transmission capacity is planned to be increased from 7,000 MW to 10,000 MW [11], with connections to The United Kingdom, Netherlands, Germany, Sweden, and Norway. Inter-regional integration alone, however, cannot create the flexibility necessary in a 100% renewable energy system [12].

Cross-sectoral integration increases the flexibility of the system by exploiting the synergies between the different sectors in the energy system, such as the electricity, gas, heating, transportation, and industrial sectors. This concept is also known as Smart Energy Systems, where a holistic approach to integration of renewable energy is taken, which proves to be much more cost-effective than transforming each sub-sector of the energy system individually [8, 9, 13]. Arguably one of the most important synergies lies between the electricity and district heating sector, as excess electricity can be converted to heat with power-to-heat technologies such as electric boilers and heat pumps [10, 14]. Storage of heat is about 100 times cheaper than storage of electricity [7], and because the losses from charging, storing, and discharging thermal storages are low, power-to-heat production and heat consumption can be decoupled [14]. This creates a significant flexible electricity demand, which can accommodate integration of large shares of renewable energy in the electricity sector in a cost-effective way [15]. At the same time, district heating is already integrated with the electricity sector, as the use of CHP is much more fuel efficient than producing heat and electricity separately [16]. The integration of the electricity and district heating sector can therefore provide flexibility in times of both excess and deficit fluctuating renewable electricity production. As such, the district heating sector will play a key role in the transition to a 100% renewable energy system [17].

1.2 Trends in the district heating sector

Heating and cooling demands account for half of the energy consumption in Europe [8, 14], of which only 10% is supplied by district heating [18]. Denmark therefore holds a unique position with 64% of the Danish households being supplied with district heating to cover the demand for space heating and hot water consumption [19]. In a district heating system, hot water is heated centrally at a district heating plant and then delivered to the consumers through a district heating grid consisting of underground piping. The losses in the district heating grid typically amounts to 20% of the produced heat [9]. However, the technical advantages of district heating, such as economy of scale and the flexibility of having a larger portfolio of units to operate, makes district heating socio-economic more feasible than individual heating solutions despite these grid losses [9]. It is therefore expected that district heating will continue to supply the majority of the Danish households with heat [5].

District heating can be produced from renewable energy sources in two ways [14]: The first is by direct conversion of renewable energy sources, such as solar heating, CHP, and heat-only boilers. The second is by conversion of electricity from renewable energy sources into heat using electric boilers and electric heat pumps. This is also called power-to-heat. Today, most district heating is produced by direct conversion of biomass, waste, and fossil fuels. 67% of the district heating produced in 2019 was cogenerated with electricity at CHP plants, while 27% was produced using heat-only boilers [2]. Solar heating contributed to 1.7% of the production of district heating, while utilization of excess heat contributed to 3.2%. Only 1.3% of the district heating in 2019 was produced using power-to-heat, and this was mostly by using electric boilers [2]. However, major investments are being made in electric heat pumps in the recent years. Between 2020 and 2021, the combined heat capacity of electric heat pumps in the district heating sector increased from 104 to 454 MW-heat. Heat pumps are expected to be the key technology to successfully coupling the electricity and district heating sector [14], as heat pumps use the principle of heat transfer to utilize low-temperature heat sources such as ambient air to generate higher temperature heat with a coefficient of performance up towards 500%.

The pull factor for the rapid expansion of power-to-heat in the district heating sector in recent years can be found in a political agreement from 2020, where the tax on electricity used for heating applications was lowered from 155 to 4 DKK/MWh-e [20]. At the same time, the increasing shares of fluctuating renewable energy in the electricity sector is causing the electricity prices to fluctuate more frequently to very low price ranges, which heat pumps can exploit to produce very cheap heat. These same trends in the electricity prices also constitute a push factor, as the feasibility of CHP is being reduced due to fewer hours with high electricity prices. This challenges the feasibility of district heating systems, as heat-only production with boilers can be achieved much cheaper in individual heating solutions [16]. To stay cost-competitive it is therefore necessary for district heating companies to participate in the sector coupling between the electricity and heating sector from a techno-economic standpoint. However, an underlying requirement for this is the ability to successfully operate an increasingly diverse portfolio of energy conversion units against increasingly uncertain and fluctuating market prices on electricity.

1.3 Operational complexities of renewable district heating

Since the cessation of the triple-tariff in 2007, CHP plants have been required to trade the produced electricity in the electricity markets [16]. Most electricity is traded in the day-ahead wholesale market as hourly bids, which occurs daily 12-36 hours in advance of the production hour. When the day-ahead market is cleared, the supply and demand is matched and the most expensive production unit that is activated determines the market price in that hour. This is also called a marginal pricing auction [21]. A district heating plant is therefore not only required to determine the most optimal operation of their energy conversion units. In order to consume or produce electricity, the district heating plants are also required to find the optimal bids to place in the day-ahead market, which in return leads to this optimal operation, before having knowledge about the clearing prices.

This makes the operation of district heating systems a stochastic optimization problem, as a decision now depends on uncertain information about the future. At the same time, energy conversion units may have starting costs or ramping periods, and thermal storages can allow the production and consumption of heat to be offset by days or even weeks [14]. To complicate the matter further, there exist additional electricity markets such as the intraday market or the balancing market, where the district heating plant can cover their losses from lost bids in the day-ahead market or earn profit by providing balancing services to the electricity grid.

It is not only the market clearing prices for electricity, which are uncertain for the district heating plant in the operational planning stage. Uncertain weather conditions such as the ambient temperature has impact on both the COP of air source heat pumps as well as the heating demand from the consumers. Many district heating plants have also included solar heating in their portfolio of units [22], which is subject to fluctuating heat production. A new trend among district heating companies is to expand the portfolio of units to include wind turbines and photovoltaics as well. This allows the district heating plant to avoid costly grid tariffs imposed by the TSO and DSO. The electricity produced by these units are consumed by power-to-heat units at the district heating plant, and thus only enters the electricity grid when the power-to-heat units are not operated. Such a concept is also called private wire operation, referring to the electricity cables between the units being owned by the district heating plant. Examples include Hvide Sande District Heating [23], which owns a nearby wind farm. The wind farm is operated in combination with a portfolio of units including natural gas boilers, natural gas CHP, an electric boiler, solar heating, as well as thermal storages. Assens District Heating purchased a nearby 1.3 MW-e wind turbine in 2017. In 2021 they are expanding their portfolio of units to also include a 2.3 MW-e electric heat pump and 5.4 MW-e photovoltaics [24]. These units will be operated together with the existing biomass boilers, biomass CHP and thermal storages. Fjerritslev District Heating is in the planning stage of investing in a wind farm with a rated capacity of 8 MW-e. The power produced by the wind turbines will be used to produce heat using the existing electric boiler, which will be operated together with two biomass boilers and a thermal storage [25].

While such hybrid district heating plants with a wide array of different energy conversion units might prove techno-economic feasible, the complexity of operating these plants also increases vastly, as the optimal operation and bids in the electricity markets depend on so many uncertainties. This is a barrier that can hinder not only a cost-effective district heating sector, but also an efficient coupling of the heating and electricity sectors [14]. This barrier can especially be difficult to overcome for the smaller and more decentral district heating plants, as they do not have the manpower and resources to cover the costs of finding optimal bidding strategies. These plants therefore rely on the existing tools on the market and how well these are able to cope with the uncertainties and complexities in renewable district heating systems.

To the knowledge of the author, energyTRADE [26] is the only commercial tool that exists for modelling and calculating the optimal operation and bids in the electricity markets for a district heating plant. It assists the plant owner in every step of the process, from collecting forecasts of electricity prices and weather data, to calculating and submitting bids, and finally creating a production plan of the optimal operation, considering the won bids. The bids are calculated in energyTRADE using the heat unit replacement method [27], which has proven to be extremely accurate at finding the optimal bids in multiple electricity markets for a traditional district heating plant with a portfolio of CHP units and heat-only boilers. However, the method struggles with finding the optimal bids for the emerging complex district heating plants with private wire operation, uncertain renewable energy production, and a combination of both power-producing and power-consuming energy conversion units.

Other methods have been proposed in existing literature. In [28], the authors propose a bidding strategy for a virtual power plant, that calculates monotonously increasing bidding curves using stochastic optimization and scenario generation. While this is a computationally demanding method, they conclude that it is compatible with the bidding framework in the day-ahead market. However, the concept of a virtual power plant is different from a district heating plant, as the latter also has to take account for a demand for heat that needs to be covered. In [29] stochastic optimization is used to calculate monotonously increasing bidding curves in a similar way, but for a Danish district heating plant that contains a wind farm, solar collectors, CHP, an electric boiler, and gas boilers. They find that stochastic optimization is suitable for calculating bids considering the uncertainty of the renewable energy production and the market prices, when compared to a simple single bid method relying on a single forecast. They also conclude that participating in the balancing market allows the district heating plant to reduce the operational costs by 8%. However, the study does not consider the starting costs and ramping periods of the energy conversion units, and the district heating plant chosen as a case study does also not include a heat pump. Furthermore, the study was conducted using data from 2017. The regulatory framework around power-to-heat and the amount of fluctuating renewable energy in the energy system has changed since then, impacting the market prices in both the day-ahead market and balancing market. Finally, the study only compares the suggested method to a single bid method.

The aim of this project is to analyze the limitations of the current state-of-the-art bidding method currently used in energyTRADE and compare it to a stochastic optimization approach. This has not been studied before. The contribution of this project is furthermore to apply the stochastic optimization approach in a different and more recent context than the previous studies. To evaluate the methods, Assens District Heating is chosen as a case study.

1.4 Assens District Heating as a case study

Assens District Heating is chosen as a case study, as it includes many of the complexities described earlier. Assens is a small city in southern Denmark with a population of 6,060. The district heating system was established in 1960 using oil boilers as the production units. In the 80s the oil boilers were supplemented by coal and woodchip boilers and in 1999 Assens District Heating invested in a 20 MW-heat CHP plant using biomass as fuel. Since then, the district heating in Assens has been almost entirely based on renewable energy sources. The plant does not own an electric boiler, but EnergiFyn owns and operates a thermal storage and an electric boiler nearby from which Assens District Heating purchases heat. Assens District Heating includes a 172 MWh-heat thermal storage in their portfolio. In 2017 Assens District Heating bought the nearby 1.3 MW-e wind turbine from a wind turbine association. To secure against decreasing and fluctuating electricity prices, a 2.3 MW-e electric heat pump using ambient air as heat source is being put into operation in spring 2021, as a supplement to the biomass CHP. This heat pump is expected to supply about half of the approximately 90,000 MWh-heat produced at the district heating plant every year. To avoid costly grid tariffs and to supply renewable electricity to the heat pump, 5.4 MW-e photovoltaics are additionally being put into operation in the summer of 2021. The combination of a heat pump and photovoltaics is a pioneering way of utilizing solar energy, as most district heating plants have invested in solar heating. What is also extraordinary is that half of the photovoltaics are facing east, and the other half is facing west. While this reduces the annual energy production, it increases the amount of hours with electricity production, allowing more load hours on the electric heat pump without having to purchase electricity form the grid. This large portfolio of diverse energy conversion units, including power-to-heat, CHP and private wire operation of fluctuating renewable energy makes the optimal operation and bidding into the electricity markets an extremely complex task. Assens District Heating therefore serves as an excellent case to analyze.

1.5 Research question

The importance of coupling the district heating sector and electricity sector has been underlined from a system-perspective, as power-to-heat and thermal storage can provide a very cost-effective way to utilize excess electricity from fluctuating renewable energy as well as providing grid balancing services. It is from the techno-economic perspective of a district heating plant also necessary to supplement heat-only boilers and CHP with power-to-heat to stay competitive with individual heating solutions, as the amount of hours with low electricity prices increases with the increasing integration of fluctuating renewable energy. Furthermore, a tendency to produce renewable electricity using private wire operation is emerging among district heating plants to avoid costly grid tariffs. These trends combined increases the complexity of operating the district heating system and participating in the electricity markets to the extent where state-of-the-art bidding tools are unable to find the optimal bids. The research in this report is focused on analyzing how to find these optimal bids. To delimit the problem, it is assumed that Assens

District Heating is a price-taker in the electricity markets, which is a reasonable simplification as the electric capacity of the production units play a negligible role in the larger Danish electricity system. The research question guiding this report is therefore as follows:

Research question: How can the optimal bids in the electricity markets be calculated for Assens District Heating as a price-taker?

A set of sub-questions are also formulated to further guide the research. It has been claimed that the current state-of-the-art bidding method is incapable of calculating the optimal bids for a complex district heating plant such as the one in Assens. It is sought to also explain why that is the case.

Sub-question #1: What are the limitations of the heat unit replacement method?

Furthermore, it is also sought to analyze how the calculated bids impact the operation of the district heating plant, compared to the optimal operation in hindsight. By analyzing this, a better understanding of the bidding methods and their strengths and limitations can be achieved.

Sub-question #2: How does the operation in a bidding framework differ from the operation with perfect information?

At last, the coupling of the district heating and electricity sector is not only important for utilizing excess renewable electricity production. The district heating sector can also provide flexibility for grid balancing services by participating in the subsequent electricity markets. It is therefore sought to analyze whether the bidding methods can accommodate this flexibility and to which extent it lowers the operational costs of the district heating plant.

Sub-question #3: What does Assens District Heating achieve by participating in multiple electricity markets?

Chapter 2

Theoretical framework

2.1 Electricity markets

2.1.1 Day-ahead market

87% of the purchased electricity and 76% of the sold electricity in Denmark is being traded in the day-ahead market, also known as the spot market [21]. The day-ahead market is operated by Nord Pool Spot and allows trading of electricity within and between many of the European countries, including all the Nordic and Baltic countries [30]. To trade in the day-ahead market, a balance responsible party can submit single hourly bids consisting of a quantity of electricity and a corresponding price, or block bids, consisting of a quantity of electricity across multiple hours and a corresponding average price [31]. It is also possible to place price-independent bids, which consist of only a quantity of electricity. Such bids are always won, no matter the spot price. The day-ahead market is cleared once per day 12 - 36 hours in advance of the hour of operation. Before 12:00 the balance responsible parties must submit their bids for the coming day. Nord Pool Spot then couples the market by matching the demand and supply of electricity [31]. This follows a marginal pricing auction, where the most expensive bid won determines the price for all the bids that have been won. However, there is imposed a lower limit of -500 EUR/MWh-e and an upper limit of 3,000 EUR/MWh-e [31]. The marginal pricing mechanism helps ensure that the production units with the least marginal costs are put into operation first, which is also known as the merit-order-effect [32]. In Figure 2.1, it can be seen how the marginal pricing auction ensure that renewable energy production with low marginal costs is put into operation first, while still being paid the same price for the produced electricity as the most expensive unit activated to meet the demand for electricity.

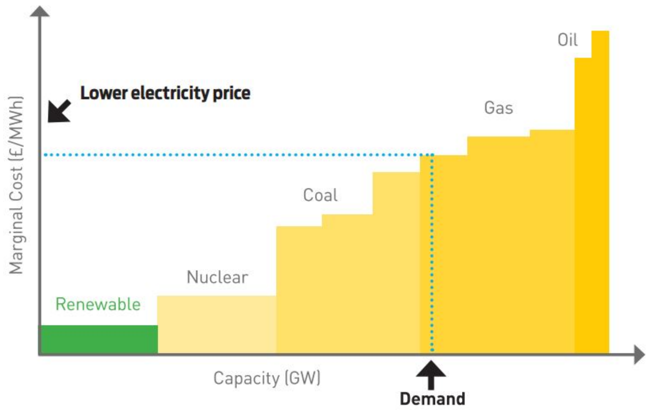

Figure 2.1. The merit-order-effect as a result of marginal pricing auctions [33]

Nord Pool Spot reveals the realized spot price an hour after gate closure at 13:00. A bid cannot be partially won, and a bid is therefore either won or lost. In the case of electricity sale, the bid is won if the realized spot price is higher than or equal to the submitted bid. In the case of electricity purchase, the bid is won if the realized spot price is lower than or equal to the submitted bid. Block bids follow the same principle, using the average price across the block instead [31].

While Nord Pool Spot includes many countries, the transmission capacity between countries and the regions within them sets a limit on the energy that can be traded. The countries participating in the day-ahead market are therefore divided into multiple price areas, in which the market price is settled taking the transmission limits between them into account. Denmark is divided into two price areas: DK1, which consists of Jutland and Fyn, and DK2 which consists of Zealand [31].

2.1.2 Intra-day market

After the day-ahead market has been realized, trading can occur in the intra-day market. Until one hour before operation, the balance responsible parties can place hourly bids or block bids in the intra-day market using what is known as the Shared Order Book [34]. The intra-day market is not an auction like the day-ahead market but matches buyers and sellers in a bilateral trade on a first come first serve basis. The price is settled using pay-as-bid and hourly bids can be partially accepted [31]. Only 2% of the total electricity trade is being traded in the intra-day [21], however this amount is expected to increase as more fluctuating renewable energy is integrated into the European electricity systems [31].

2.1.3 Regulating market

Imbalances from the planned production and consumption of electricity will inevitably occur. It is the responsibility of the TSO, which in Denmark is Energinet, to maintain the stability of the transmission grid. This is achieved by activating reserve capacity [35]. There exist three types of reserves: primary, secondary, and tertiary.

The primary and secondary reserves are similar in the sense that they are both activated automatically or by Energinet. Their purpose is to provide ancillary services for respectively short-term and medium-term deviations in the stability of the grid. Balance responsible parties can bid the availability of their units into these reserves for a fixed period of time [35].

The tertiary reserves are manual reserves, which the balance responsible parties can activate on behalf of Energinet to provide more long-term ancillary services. Many of the imbalances that arise from for example the uncertainty of fluctuating renewable energy production can be determined more accurately as the hour of operation is approaching. Tertiary reserves are therefore activated in each price area pro-actively to avoid or limit the use of the more expensive primary and secondary reserves [35]. The tertiary reserves make up for 70% of the ancillary services activated by Energinet [35]. To participate as a tertiary reserve, the balance responsible parties can place bids in the regulating market.

A distriction can be made between availability bids, where energy conversion units are reserved as stand-by capacity, and activation bids, where a won bid always results in a trade of electricity. A balance responsible party can place both availability bids and activation bids. If an availability bid is won, the balance responsible party must place the bidded amount as activation bids [36].

Two types of situations can occur in the system: either the sum of imbalances leads to a surplus of energy or a deficit of energy. When there is a surplus of energy, down regulation is activated, which is achieved by producing less or consuming more electricity. When there is a deficit of energy, up regulation is activated, which is achieved by producing more or consuming less electricity. In the regulating market, balance responsibility parties can place both types of regulating bids. Gate closure for the regulating market is 45 minutes before the hour of operation and only hourly bids can be placed with a minimum capacity of 5 MW-e [36]. When Energinet activates regulating power, the principle of marginal pricing is used for all the accepted bids. However, the price for up regulation can never be lower than the spot price, and the price for down regulation can never be higher than the spot price [36].

In some hours both up regulation and down regulation may be activated in the same price area to avoid local congestion in the grid. In this case, two different regulating prices are calculated using marginal pricing [36]. Sometimes local congestion can also lead to special regulation, where the marginal pricing mechanism is disobeyed to avoid interfering with the regulating settlement price in the entire price area. Special regulation is settled as pay-as-bid. Almost all special regulation in Denmark occurs in the DK1 price area due to technical problems in the transmission grid of northern Germany [36].

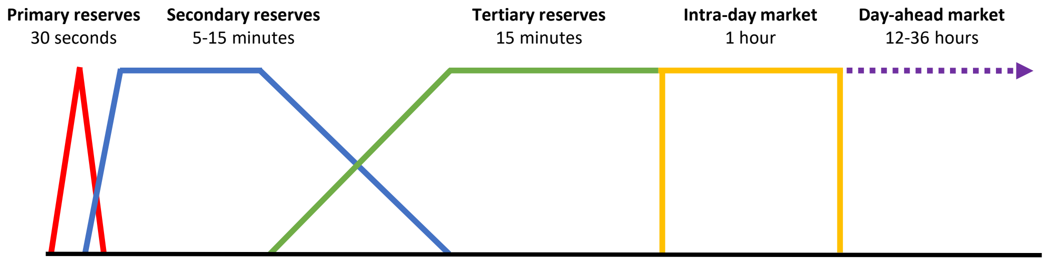

Figure 2.2. The different ancillary services and electricity markets in relation to when they play a role in balancing the grid [37]

In Figure 2.2, the different ancillary services and electricity market are placed on a timeline to give an overview of when they play a role in balancing the grid. The primary reserves are used to provide immediate ancillary services for the next couple of minutes. If the imbalance persists, the secondary reserves are activated, until the cheaper tertiary reserves can be manually activated. The intra-day market plays a role in balancing the grid and matching supply and demand for the next hour and until the first hour that has not yet been realized in the day-ahead market.

2.1.4 Settlement prices for imbalances

The imbalances that the balance responsible parties are not able to avoid by trading in the subsequent electricity markets after the day-ahead market, may cause the need for Energinet to activate the primary, secondary or tertiary reserves [35]. When the hour of operation has passed, the actual consumption and production of electricity is measured. If no regulating power was activated in this hour, the imbalance price is equal to the spot price [36]. If regulating power was activated, a two-price settlement model is used for production and consumption imbalances separately. In the two-price model, imbalances that contribute to the system imbalance are settled with the regulating price, while imbalances that decreases the system imbalance are settled with the spot price. This asymmetrical model leads to an income for Energinet, which is used to cover the costs for primary and secondary reserves [36]. However, by the end of 2021, the two-price model is expected to be replaced with a one-price model instead [38]. This will create symmetrical imbalance prices, allowing consumption and production imbalances to cancel each other out.

2.2 Stochastic unit commitment

The unit commitment problem is a decision problem concerning the optimal on/off state of a portfolio of energy conversion units. In the traditional formulation of this decision problem, the objective is to minimize the fuel costs while meeting a required demand for energy and taking account for various constraints such as reserve capacity, starting costs and ramping periods of the units. An example of a basic unit commitment problem can be seen in expressions 2.1 to 2.3:

$$\min \quad \sum_{g \in G} \sum_{t \in T} c_g \cdot p_{g,t} \tag{2.1}$$

$$\text{s.t.} \quad \sum_{g \in G} p_{g,t} \geq d_t, \qquad \forall t \in T \tag{2.2}$$

$$p_{g,t} \in \{0, 1\}, \qquad \forall g \in G, t \in T \tag{2.3}$$

In expression 2.1, the objective function is to minimize the generating costs, c, for all generating units in G over all time periods in T. The first constraint in equation 2.2 requires the sum of the generated power, p, by all generating units to be greater than the demand, d, for all time periods in T. In expression 2.3, the output of all the generating units are constrained to be binary values in all time periods.

One of the most widely used approaches for solving unit commitment problems is by using mixed-integer linear programming [39]. The mixed-integer part refers to the possibility of combining continuous and integer decision variables in the problem formulation. Modelling the on/off state of an energy conversion unit is a binary decision variable, which is a subset of integer decision variables that can only take the values 0 or 1. Using mixed-integer linear programming for solving the unit commitment problem is a widely used approach because it allows a simple formulation of the problem, it is able to secure global optimality or an optimal solution within a specified tolerance gap, and because a wide array of commercial and non-commercial solvers exist, that are specialized at solving mixed-integer linear problems in a computationally efficient way [39]. The traditional unit commitment problem and the methods for solving it has played a crucial role in minimizing the amount of fossil energy used in the energy system by scheduling the energy conversion units in the most fuel-efficient way [39].

In modern deregulated energy markets, the energy conversion units do not only need to be scheduled to reduce operating costs, but they also must participate in the competitive markets by placing bids for production or consumption. This has led to the reformulation into a profit-based unit commitment problem, where the objective instead is to maximize the revenue from participating in the market [39]. The profit-based unit commitment problem is on the contrary to the traditional cost-based unit commitment problem often a mixed-integer non-linear problem, which is significantly harder to solve. Another complexity of the profit-based unit commitment problem is the uncertainty of the market prices, which are often not known when the decision must be made. This makes the profit-based unit commitment problem a stochastic unit commitment problem, referring to the uncertainty of one or more parameters in the problem formulation. In expressions 2.4 and 2.5, the traditional unit commitment is problem is reformulated into a stochastic unit commitment problem.

$$\min \quad \sum_{g \in G} \sum_{t \in T} p_{g,t} \cdot m_t - p_{g,t} \cdot c_g \tag{2.4}$$

$$p_{g,t} \in \{0,1\}, \qquad \forall g \in G, t \in T \tag{2.5}$$

In the reformulation, the requirement for covering a certain demand has been removed. Instead, a revenue for producing, m, has been added in the objective function. The revenue for producing expresses the uncertain market price, which is not yet realized when the decision must be made. The stochastic unit commitment can therefore not be solved in this form.

A widely used approach is to instead reduce the stochastic unit commitment problem to a deterministic problem, by using a forecast for the uncertain market price and assume this forecast to be entirely correct [40]. The formulation in expressions 2.4 and 2.5, can then be solved, since the revenue, m, is now assumed to be known. If the forecast is capable of accurately predicting the realized market prices, this approach may produce good solutions [41].

Another, but less used approach, is to solve the stochastic unit commitment problem using scenario-generation [42]. While the market price may be uncertain, we may have an idea about the distribution of this random variable by analyzing historical data. Using this knowledge, alternative scenarios for the market price can be generated. Each of these scenarios result in a deterministic equivalent to the stochastic unit commitment problem. These deterministic equivalents can then be combined into one huge deterministic unit commitment problem, for which a global optimal solution can be found using mixed-integer linear programming. The reformulation of the stochastic unit commitment problem into a deterministic problem using scenario generation can be seen in expressions 2.6 and 2.7:

$$\min \quad \sum_{s \in S} \sum_{g \in G} \sum_{t \in T} p_{g,t} \cdot m_{s,t} - p_{g,t} \cdot c_g \tag{2.6}$$

$$p_{g,t} \in \{0,1\}, \qquad \forall g \in G, t \in T \tag{2.7}$$

In the reformulation, a sum over the scenarios, S, is included in the objective function, while the revenue, m, is made specific for each scenario S and for each time period in T. In this formulation of the problem, the decision variables are not specific to each scenario. This means that the optimal schedule of the units is the one that results in the highest average value across all scenarios. In other words, the solution maximizes the expected value. When the generated scenarios, S, are only a sample of all possible outcomes, this technique is known as Sample Average Approximation [43]. It is rarely practical to generate all possible scenarios of the future. For a planning horizon of 24 hours, where the hourly spot price is assumed to take either a low, medium, or high value in each hour independently, a total of 3^{24} (282 billion) unique scenarios exist, which makes the mixed-integer linear problem intractable. An important attribute of solutions resulting from Sample Average Approximation is that they are almost never optimal in hindsight. The solution is instead a balanced solution that in hindsight is never the best but also never the worst [41].

The approach of using a single forecast can be seen as a subcategory of the scenario-based approach, where only one scenario is generated. The generation of multiple scenarios and the combination of their deterministic problems into one large unit commitment problem therefore incorporates more knowledge into the decision problem. If the uncertainties of the stochastic variables are small, the extra computational burden of the scenario-based approach may not be worth the slightly improved solution. However, as more fluctuating renewable energy is being integrated into the portfolio of units of the decision-maker as well as in the surrounding system, the difference in the solution quality of the two approaches will diverge [42].

An important assumption when formulating stochastic unit commitment problems is the number of stages in the problem [39, 42]. A stochastic unit commitment problem may constitute of multiple uncertain variables that are realized at different time periods in the planning stage. The simplest form of stochastic unit commitment problems is a two-stage model. In the first stage, a decision has to be made with the variables still being uncertain. Once the decision has been made, the problem moves to the second stage where the uncertain variable is realized. An example of this could be the bidding into the electricity as the first stage problem. Once the bids have been submitted, the electricity price is realized the problem moves on to the second stage, where the decision is then to find the optimal operation of the energy conversion units, considering the bids won. Stochastic unit commitment problems can have any number of stages, with different uncertain variables being realized at different stages. These types of problems are called multi-stage problems. However, the problem can quickly become intractable with multiple stages.

2.3 Heat unit replacement method

The state-of-the-art heat unit replacement method [27] that is currently being used to calculate optimal bids for district heating plants in sequential electricity markets in energyTRADE is a special instance of the stochastic unit commitment problem. The heat unit replacement bidding method does not use scenario decomposition and relies on a single forecast for finding the optimal schedule of the units. Instead, it exploits a structure of the problem to allow for calculating bidding curves and placing bids even in hours that the model does not expect to win. This is achieved by iteratively solving variations of the same deterministic unit commitment problem with different constraints for the units. The underlying assumption in the heat unit replacement method is that the demand for district heating can always be covered by heat-only boiler production, which have operation costs independent from the uncertain electricity price.

The first step of the heat unit replacement method is to solve the traditional unit commitment problem for a given planning horizon considering heat-only production on the boilers only, by restricting the trade on the electricity markets. An important assumption is that the energy content in the thermal storage at the end of the planning horizon must be equal or higher than the energy content in the beginning of the planning horizon. This formulation avoids defining the costs of discharging the thermal storage. The first step results in an optimal dispatch of the heat-only boilers independent of the market prices.

In the second step, the heat-only boilers are constrained to produce at least the same amount of heat as in the first step in all hours, while trading on the electricity markets is at the same time allowed. This makes it more feasible to produce heat on the CHP in hours with high forecasted electricity prices. However, because the heat-only boilers are constrained with a minimum operation, there is no room for CHP production. In the unit commitment problem, the most expensive heat-only boiler is then disabled, restricting any production of heat on this unit. This creates a deficit heat production, which the CHP must cover, regardless of whether it is more cost-effective than the disabled boiler. The heat production from the CHP may not occur in the same hour as the replaced heat, as the CHP can utilize the thermal storage to operate according to the forecasted electricity prices. This principle is then repeated in an iterative way, replacing the most expensive boiler until either all heat-only boilers have been disabled or until the problem becomes infeasible.

In the third step, the bids are calculated. Each of the solutions from the iterative unit commitment problems in step 2 contain an increasing amount of CHP production. The bidding prices for these productions are found using the costs of operating the CHP minus the opportunity cost of not operating the CHP. The opportunity cost is the operating costs of the heat-only boiler that the CHP replaced, as the heat must be produced in one way or another.

The heat unit replacement bidding method has proven to place very competitive bids for traditional district heating plants with a combination of CHP units and heat-only boilers. The method produces a bidding curve that can have as many steps as the number of heat-only boilers that can be replaced. The method furthermore places bids in hours that are not expected to be won, while never placing bids that would result in higher operating costs than producing heat on the heat-only boilers.

The method can be extended to enable participation in sequential electricity markets using the principle of changed opportunities in the spot market. The bidding price is here found for a single hour by comparing the objective value between the optimal unit commitment problem, and the unit commitment problem where the CHP unit has the opposite state. The difference in the objective values corresponds to the changed opportunity in the spot market. If the opposite state of the CHP resulted in less heat being produced, a down-regulation bid was placed, and the heat would have to be produced by a heat-only boiler or the CHP at a later point, where the spot market has not yet been realized. If the opposite state of the CHP resulted in more heat being produced, an up-regulation bid was placed, and less heat would have to be produced by the heat-only boilers or the CHP at some point in the future instead. The bid in the sequential electricity markets is in other words calculated such that the change in unit commitment does not lead to a lower expected objective value in the planning horizon.

While the heat unit replacement bidding method is very competitive for calculating bids for a traditional district heating plant, the method relies on exploiting a certain structure of the problem, namely that units can be divided into heat-only producing units independent of the market, and market-dependent heat producing units. However, for a district heating plant such as the one in Assens, units that produce only power also exist, and the addition of power-to-heat units allow for both purchasing and selling electricity. It therefore becomes impossible to distinguish between market-dependent and market-independent units, and it also becomes impossible to define the opportunity cost of not operating a unit. Because the underlying structure of the problem can no longer be exploited in the same way, it leads to having to place price-independent bids instead which are very sensitive to bad forecasts.

Chapter 3

Methodology

3.1 Case study

As described in section 1.4, Assens District Heating is chosen as a case study. A case study can help the researcher achieve context-dependent knowledge that a more general and theoretical approach cannot [44]. Knowledge obtained from conducting a case study can also be generalized to the general phenomena, when using a proper strategy for selecting the case [44]. The type of case that Assens District Heating constitutes in this report can be classified as both an instrumental case and an extreme case. It is an instrumental case in the sense that it is not an understanding of the case itself that is the most important objective of the research, but the fact that it facilitates an understanding of a larger and more complex problem [45]. Without an instrumental case it would be difficult to analyze different bidding methods, which due to their relation to technology and the energy market frameworks are inherently context-dependent already. The case is also an extreme case in the sense that Assens District Heating is an unusual district heating plant acting as a frontrunner in the transition to a 100% renewable energy system. Because it is an extreme case, it serves well for testing the limits of a bidding method, as extreme cases are especially good for obtaining new information [44].

While Assens District Heating constitutes the only case in this report, a simplified and hypothetical variation of the case is also studied. In this hypothetical case, hereafter referred to as the simple case, the district heating plant is reduced to only containing wood chip boilers, an electric heat pump and a thermal storage. The purpose of this case is to have a case which the heat unit replacement bidding method can be applied to, such that the limitations of the method can be shown, and such that the competitiveness of the other bidding methods can be validated before applying them the case of Assens District Heating. The simple case therefore also acts as an instrumental case, but it is not an extreme case. The bidding methods are first applied to the simple case and analyzed in this more comprehensible context, before scaling the problem and analyzing the full case of Assens District Heating, hereafter referred to as the full case.

3.2 Mathematical modelling

It is not possible to test the bidding methods in practice at a real district heating plant by trial and error. To compare the different bidding methods, a mathematical model of the district heating plant in a sequential electricity market bidding framework is instead developed. A mathematical model is a simplified abstraction of a real-world phenomenon, and it can be used to predict the outcome of different decisions [46]. This is illustrated in Figure 3.1.

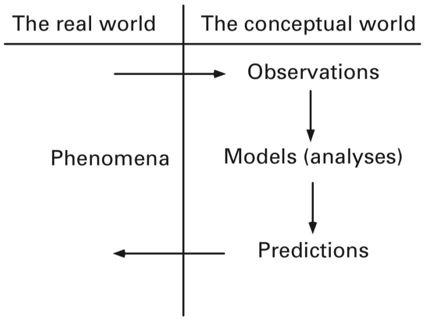

Figure 3.1. The relation between mathematical modelling in the conceptual world and the real world phenomenon [46]

As it can be seen in Figure 3.1, mathematical modelling starts with an interpretation of the real world, using observations. These observations are used to formulate a model in the conceptual world. If the model replicates the most important attributes of the real-world phenomenon, testing different input data on the model can create predictions about what would happen in the real world. Following this methodology, it is possible to test various bidding methods on a mathematical model of a district heating plant. To simulate the operation of a district heating plant in an electricity market bidding framework, a number of assumptions are made in the interpretation of the real-world phenomena into an operational planning model.

3.2.1 Interaction with the electricity markets

It is assumed that the district heating plant is a price-taker that can place bids in the day-ahead market and activation bids on the regulating market. Assens District Heating is located in the DK1 price area. Only one extra electricity market is considered to keep the model simple. Activation bids on the regulating market is chosen, as this is the most used ancillary service by Energinet [36] and because historical data about this market can be acquired. The minimum bidding amount on the regulating market is disregarded. Special regulation is not included in the model, and in the case of both upward and downward regulation in the same hour, bids are only accepted for the dominant direction in the price area.

If the operational planning model places bids that end up causing imbalances, a one-price settlement method is used, as Energinet will begin to use this approach by the end of 2021 [38]. The imbalance settlement price is the regulating settlement price for the dominant direction in the system. If no regulating power is activated, imbalances are settled with the spot price.

The model is discretized into hourly time steps to resemble the hourly bids in the day-ahead-market. It is assumed that regulating bids are activated for an entire hour at a time. Bids are submitted to the day-ahead market every day after the operation of the 11th hour and before the operation of the 12th hour begins. In other words, the bids are submitted at exactly 12:00 which is gate closure for the day-ahead market. The market is then coupled instantaneously, and the spot price is realized for the following day, still before the operation of the 12th hour has begun. This assumption is made to simplify the model formulation. Likewise, regulating bids are placed just before the hour of operation and realized at once.

3.2.2 Data collection

The data for the realized spot market prices, regulating prices, up regulation amount and down regulation amount are obtained from [47]. The weather data for aggregated irradiance, wind speed and ambient temperatures are obtained from [48], for the coordinates 55.22N, 9.84E. Data about the efficiency and capacity of energy conversion units as well as the economic data such as tariffs, fuel costs etc. are derived from the energyPRO-model provided by Assens District Heating. It is expected that the plant manager has the most accurate information about these important parameters.

3.2.3 Heat demand

The operation of the district heating grid is not included in the model. In this report, the heat demand therefore refers to the heat being fed into the district heating grid from the district heating plant. The heat demand is modelled using degree-hours calculated from the ambient temperature with a reference of 17°C. The annual demand is assumed to be 96,000 MWh-heat, with 60% of the heat demand being degree-hour dependent to cover the space heating demand. The remaining 40% of the demand is degree-hour independent, covering grid losses and hotwater consumption. For a specific hour, the heat demand, d, depending on the ambient temperature, t_a, is calculated as follows:

$$d = 0.9517\frac{MW}{^{\circ}C} \cdot max(17^{\circ}C - t_a, 0^{\circ}C) + 4.3836MW \tag{3.1}$$

3.2.4 Energy conversion units

The model is formulated as a mixed-integer linear program, and all the units must therefore be modelled in linear or integer terms. It is assumed that all the units are operated for whole hourly time steps, and that the units have no ramping periods. For the simple model, the following units are assumed to be included in the portfolio of operating units:

- A thermal storage with a capacity of 80 MWh-heat
- Three woodchip boilers with a combined capacity of 17 MW-heat
- An electric heat pump with a capacity of 3.5 MW-e, operated using ambient air as heat source

For the full model of Assens District Heating, the following units are assumed to be included in the portfolio of operating units:

- A thermal storage with a capacity of 172 MWh-heat
- Three woodchip boilers with a combined capacity of 17 MW-heat
- An electric heat pump with a capacity of 2.3 MW-e, operated using ambient air as heat source
- An electric boiler with a capacity of 15 MW-e
- A woodchip CHP plant with a capacity of 20 MW-fuel
- A wind turbine with a rated capacity of 1.307 MW-e
- Photovoltaics with a capacity of 5.4 MW-e, where half is facing east, and half is facing west

An overview of all the units in the full case and how they are interconnected can be seen in Figure 3.2.

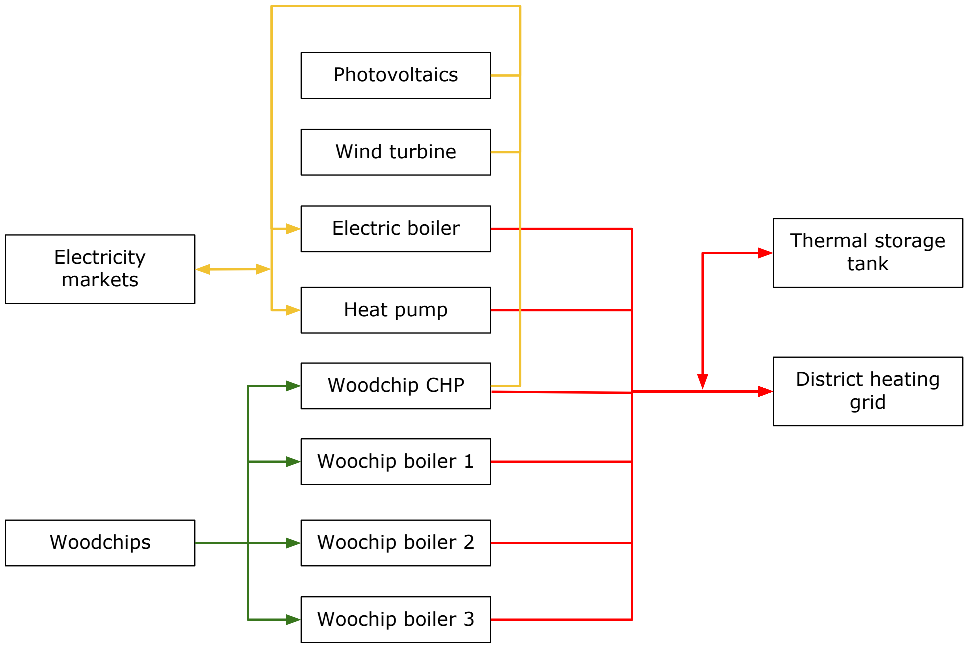

Figure 3.2. An overview of the full case with Assens District Heating

For the thermal storage, heat losses are not included in the model. At the beginning of the simulation, the thermal storage starts being half full. At the end of the simulation, the thermal storage must again be exactly half full. This constraint is made to avoid issues comparing multiple simulations, as it is difficult to set a value on the energy left in the thermal storage.

The woodchip boilers are modelled with a continuous decision variable, allowing any production of heat within the specified capacity. The fuel consumption is not modelled and a cost of producing heat is instead used.

The electric heat pump is also modelled with a continuous decision variable, allowing any consumption of electricity within the specified capacity. The corresponding heat production is modelled using a Lorentz-COP with a constant efficiency of 39.6%. The heat source is equal to the ambient temperature and is cooled by 5°C. The heat sink is the return temperature of 35°C, which is heated to the forward temperature of 70°C. The reader is referred to [49] for the exact calculation methodology used.

The electric boiler is modelled with a continuous decision variable, allowing any consumption of electricity within the specified capacity. The corresponding heat production is calculated using a constant efficiency of 99%.

The woochip CHP plant is modelled by dividing it into a base load and a production load. The base load is assumed to always be operated, consuming 1.92 MW-fuel, and producing 1.44 MW-heat. Electricity is also produced, but this is used for self-consumption. The production load is modelled using a continuous decision variable to determine the fuel consumption, with a minimum operation load of 25% of maximum capacity. A binary decision variable defines whether the production load is on, and a start-up is assumed to incur a cost of 500 DKK, expressing the costs in man-power and reduced efficiency during the ramping, which in return is not modelled. The CHP can be operated as a CHP unit or in bypass-mode, producing heat-only. It is assumed that any combination of these two modes is possible within the same hour, with the capacity for fuel consumption being the common constraint. The domain of the continuous decision variable for fuel consumption can be seen in Figure 3.3.

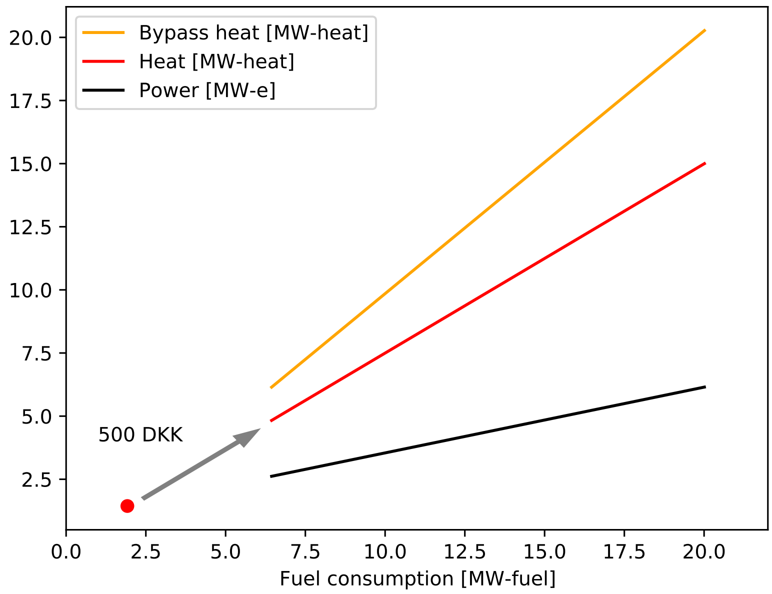

Figure 3.3. The domain of the fuel consumption of the CHP and the corresponding heat and power production

In Figure 3.3, the red dot depicts the heat production for base load operation. The production load can be increased for a starting cost of 500 DKK as the grey arrow shows. This allows a continuous fuel consumption between 6.44 and 20 MW-fuel. The CHP can be operated producing heat and power, shown with the red and black lines, or producing bypass-heat only, shown with the orange line. While this model is a simplification of a typically non-linear CHP plant, Assens District Heating is only an instrumental case for studying the bidding method. This simplification is therefore sufficient, while still expressing the complexity that binary decision variables and interdependency of operation hours entail.

The wind turbine is modelled using data about windspeed, a power curve and a binary decision variable, allowing the wind turbine to be fully curtailed. The power curve used is shown in Figure 3.4:

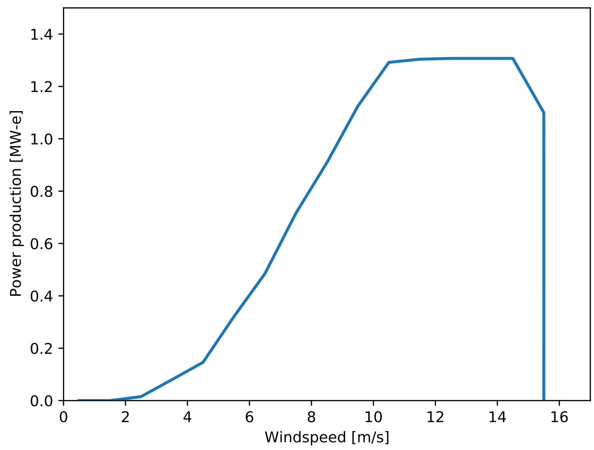

Figure 3.4. The power curve of the wind turbine relative to the wind speed

The photovoltaics are modelled with the state-of-the-art method used in energyPRO. The reader is referred to [50] for the exact calculation methodology used. The power output is based on the aggregated irradiance and ambient temperature, using an inclination of 35°. The photovoltaic module has a maximum power of 240 W, a temperature coefficient of -0.38%/°C and a nominal cell operating temperature of 45°C. Aggregated losses from the module are assumed to be 10%, and no effects of array shading are included. Half the photovoltaics are facing east, with a -90° deviation from south, and half the photovoltaics are facing west, with a 90° deviation from south.

3.2.5 Simulation of the operation

It is desired to analyze the bidding methods in a simulation period with recent data, to perform the analysis in a context with as much renewable energy integrated in the energy system as possible. Therefore, the simulation is carried out using data from 2020. It is however not possible to simulate more than a couple of weeks of operation due long computation times and a limited time frame to perform the analysis. A week in each season could be simulated to represent the seasonal effects on the operation of the district plant. However, this would lead to four very small samples, where the variations between the bidding methods would not develop enough to create significant deviations in the operation. Four consecutive weeks from October 1st 2020 to October 29th 2020 are instead chosen, as the solar irradiance is still significant at this time of the year, while the ambient temperature is low enough to cause a degree-hour dependent heat demand.

A planning horizon of five days is used in the simulation. The planning horizon is the amount of time that the model looks ahead when placing bids in the electricity markets and performing the optimal unit commitment. A long planning horizon leads to a more optimal unit commitment, as the optimal bids for the coming day are then placed while considering future conditions. This allows the district heating plant to for example fill up the thermal storage in preparation for a peak load. However, a long planning horizon also considerably increases the computational burden. A five days planning horizon is assumed to strike a balance between computational speed and optimal operation, based on the findings in [27].

The model is formulated as a three-stage mixed-integer linear program, which is solved for each hour in the planning horizon. In between the stages, new data is revealed or generated. The simulation is initialized as follows:

1. **First stage MILP:** The simulation starts on 30th of September at 12:00. Calculate and place bids into the day-ahead market for the 24 hours in the following day.
2. The spot price as well as which bids are won for the 24 hours the following day is instantly revealed.
3. The time is then fast-forwarded to the beginning of the simulation period at 00:00 on October 1st.
4. Generate scenarios and prognoses for the spot prices for all timesteps in the planning period where the market has not been cleared yet.

The following loop of actions are then repeated until the time is 00:00 on October 29th:

1. The actual weather data is revealed for the coming hour.
2. Using these values, generate scenarios and prognoses for weather data for the planning horizon.
3. Generate scenarios and prognoses for the spot prices for all timesteps in the planning period where the market has not been cleared yet, using the last known value as a starting point.
4. **First stage MILP:** If the current time is 12:00, calculate and place bids in the day-ahead market for all 24 hours in the following day.
5. If the current time is 12:00, the spot price as well as which bids are won for the 24 hours the following day is instantly revealed.
6. Generate scenarios for regulating bids in both directions for the coming hour
7. **Second stage MILP:** Calculate and place bids in the regulating market for the coming hour.
8. The regulating price and direction is then instantly revealed and it is known whether the bids are won.
9. **Third stage MILP:** Calculate the unit commitment and optimal operation of the coming hour.
10. Calculate the costs of imbalances that occured from this optimal operation.
11. Update the initial energy content in the thermal storage and the initial unit commitment variable defining whether the CHP is on or off.
12. Increment time by 1 hour

The same MILP formulation is used for all the analyzed bidding methods, as the heat unit replacement bidding method or a simple price independent bidding method can be understood as a stochastic unit commitment problem with 1 scenario. The same MILP formulation is also used for every stage in the three-stage MILP. The difference between the stages lies in which of the parameters that are uncertain and therefore expressed with prognoses or scenarios to create a deterministic problem, and which of the parameters that have obtained the actual real values.

3.2.6 MILP formulation

Sets

T	set of time periods in the planning horizon
X	set of time periods in the planning horizon including the previous hour
S	set of scenarios

Variables

$TS_{s,t}$	$s \in S, t \in X$	thermal storage content
$HP_{s,t}$	$s \in S, t \in T$	unit commitment for heat pump
$WCB_{s,t}$	$s \in S, t \in T$	unit commitment for woodchip boiler
$EB_{s,t}$	$s \in S, t \in T$	unit commitment for electric boiler
$WT_{s,t}$	$s \in S, t \in T$	unit commitment for wind turbine
$CHP^{on}_{s,t}$	$s \in S, t \in X$	binary unit commitment for CHP
$CHP^{start}_{s,t}$	$s \in S, t \in T$	whether CHP is started
$CHP^{fuel}_{s,t}$	$s \in S, t \in T$	continuous unit commitment for CHP fuel consumption
$CHP^{prod}_{s,t}$	$s \in S, t \in T$	continuous unit commitment for CHP production
$CHP^{bypass}_{s,t}$	$s \in S, t \in T$	continuous unit commitment for CHP bypass
$grid^{import}_{s,t}$	$s \in S, t \in T$	imported electricity from grid
$grid^{export}_{s,t}$	$s \in S, t \in T$	exported electricity to grid
$spot^{trade}_{s,t}$	$s \in S, t \in T$	traded electricity on the spot market
$imbalance^{deficit}_{s,t}$	$s \in S, t \in T$	imbalance from deficit consumption of electricity
$imbalance^{surplus}_{s,t}$	$s \in S, t \in T$	imbalance from surplus consumption of electricity
$reg^{down}_{s,t}$	$s \in S, t \in T$	down regulation
$reg^{up}_{s,t}$	$s \in S, t \in T$	up regulation

Parameters

$down^{price}_{s,t}$	price for down regulation
$up^{price}_{s,t}$	price for up regulation
$spot^{price}_{s,t}$	spot price
C_{HP}	O&M costs for producing heat on heat pump
C_{WCB}	O&M and fuel costs for producing heat on woodchip boiler
C_{EB}	O&M costs for producing heat on electric boiler
C_{WT}	O&M costs for producing electricity on wind turbine
C_{oil}	costs for processing oil used in the CHP
C_{CHP}	O&M and fuel costs for the CHP
$C_{CHP^{start}}$	costs for increasing CHP load past base load
C_{tariff}	various tariffs and taxes for importing electricity
$C_{imbalance}$	a constant value of 200 DKK/MWh-e
$CHP^{on}_{initial}$	initial state of the CHP
$TS_{initial}$	initial energy content in the thermal storage
$f(wind_{s,t})$	wind power per rated capacity as a function of wind speed
$g(irr_{s,t}, ambient_{s,t})$	solar power per rated capacity as a function of aggregated irradiance and ambient temperature
$h(ambient_{s,t})$	heat demand to be delivered to the district heating grid as a function of ambient temperature
$j(ambient_{s,t})$	COP of the heat pump as a function of ambient temperature
$\overline{WCB}_{heat}$	thermal capacity of woodchip boilers
$\overline{EB}_{heat}$	thermal capacity of electric boiler
$\overline{EB}_{power}$	electric capacity of electric boiler
$\overline{WT}_{power}$	rated capacity of wind turbine
$\overline{WT}_{power}$	rated capacity of wind turbine
$\overline{HP}_{power}$	electric capacity of heat pump
$\overline{CHP}^{base}_{fuel}$	fuel consumption of CHP base load
$\overline{CHP}^{base}_{heat}$	heat production of CHP base load
$\underline{CHP}^{fuel}$	minimum fuel consumption when not in base load
$\overline{CHP}^{prod}_{fuel}$	capacity of fuel consumption when producing CHP
$\overline{CHP}^{prod}_{heat}$	capacity of heat production when producing CHP
$\overline{CHP}^{prod}_{power}$	capacity of electricity production when producing CHP
$\overline{CHP}^{bypass}_{fuel}$	capacity of fuel consumption when producing in bypass-mode
$\overline{CHP}^{bypass}_{heat}$	capacity of heat production when producing in bypass-mode

Objective

The objective function to be minimized is the sum of operation costs minus revenue for all timesteps in the planning horizon and for all scenarios. Every scenario has the same weight. The revenue consists of sale of electricity on the day-ahead market, sale of electricity on the regulating market, and refunded imbalances for deficit consumption of electricity. The expenses consist of operation and maintenance costs for the units, fuel costs, starting costs on the CHP, various tariffs and taxes imposed on import of electricity, purchase of electricity on the day-ahead market, purchase of electricity as down regulation, and imbalances for surplus consumption of electricity. The refunded value or expense for having imbalances is defined in such a way, that it is always more profitable to trade the correct amount of electricity instead.

$$
\begin{aligned}
\min \quad \sum_{s \in S} \sum_{t \in T} \Big[\quad & reg^{down}_{s,t} \cdot down^{price}_{s,t} - reg^{up}_{s,t} \cdot up^{price}_{s,t} && (3.2)\\
& + HP_{s,t} \cdot \overline{HP}_{power} \cdot j(ambient_{s,t}) \cdot C_{HP} && (3.3)\\
& + WCB_{s,t} \cdot \overline{WCB}_{heat} \cdot C_{WCB} && (3.4)\\
& + EB_{s,t} \cdot \overline{EB}_{heat} \cdot C_{EB} && (3.5)\\
& + WT_{s,t} \cdot \overline{WT}_{power} \cdot f(wind_{s,t}) \cdot C_{WT} && (3.6)\\
& + \overline{CHP}^{base}_{fuel} \cdot C_{CHP} && (3.7)\\
& + CHP^{bypass}_{s,t} \cdot \overline{CHP}^{bypass}_{fuel} \cdot C_{CHP} && (3.8)\\
& + CHP^{prod}_{s,t} \cdot \overline{CHP}^{prod}_{fuel} \cdot C_{CHP} && (3.9)\\
& + CHP^{prod}_{s,t} \cdot \overline{CHP}^{prod}_{power} \cdot C_{oil} && (3.10)\\
& + CHP^{start}_{s,t} \cdot C_{CHP^{start}} && (3.11)\\
& + grid^{import}_{s,t} \cdot C_{tariff} && (3.12)\\
& + spot^{trade}_{s,t} \cdot spot^{price}_{s,t} && (3.13)\\
& - imbalance^{deficit}_{s,t} \cdot (down^{price}_{s,t} - C_{imbalance}) && (3.14)\\
& + imbalance^{surplus}_{s,t} \cdot (up^{price}_{s,t} + C_{imbalance}) \quad \Big] && (3.15)
\end{aligned}
$$

Constraints

The first constraints define the domain of the decision variables.

$$TS_{s,t} \in [0, \overline{TS}], \quad \forall s \in S, t \in T \tag{3.16}$$

$$HPs, t \in [0, 1], \quad \forall s \in S, t \in T \tag{3.17}$$

$$WCBs, t \in [0, 1], \quad \forall s \in S, t \in T \tag{3.18}$$

$$EBs, t \in [0, 1], \quad \forall s \in S, t \in T \tag{3.19}$$

$$WTs, t \in \{0, 1\}, \quad \forall s \in S, t \in T \tag{3.20}$$

$$CHP^{on}_{s,t} \in \{0, 1\}, \quad \forall s \in S, t \in T \tag{3.21}$$

$$CHP^{start}_{s,t} \in \{0, 1\}, \quad \forall s \in S, t \in T \tag{3.22}$$

$$CHP^{fuel}_{s,t} \in [0, 1], \quad \forall s \in S, t \in T \tag{3.23}$$

$$CHP^{prod}_{s,t} \in [0, 1], \quad \forall s \in S, t \in T \tag{3.24}$$

$$CHP^{bypass}_{s,t} \in [0, 1], \quad \forall s \in S, t \in T \tag{3.25}$$

$$grid^{import}_{s,t} \in \mathbb{R}_{\geq 0}, \quad \forall s \in S, t \in T \tag{3.26}$$

$$grid^{export}_{s,t} \in \mathbb{R}_{\geq 0}, \quad \forall s \in S, t \in T \tag{3.27}$$

$$spot^{trade}_{s,t} \in \mathbb{R}, \quad \forall s \in S, t \in T \tag{3.28}$$

$$imbalance^{deficit}_{s,t} \in \mathbb{R}_{\geq 0}, \quad \forall s \in S, t \in T \tag{3.29}$$

$$imbalance^{surplus}_{s,t} \in \mathbb{R}_{\geq 0}, \quad \forall s \in S, t \in T \tag{3.30}$$

$$reg^{down}_{s,t} \in \mathbb{R}_{\geq 0}, \quad \forall s \in S, t \in T \tag{3.31}$$

$$reg^{up}_{s,t} \in \mathbb{R}_{\geq 0}, \quad \forall s \in S, t \in T \tag{3.32}$$

The following constraints model the operation of the CHP. The CHP can only consume more fuel than it does under base load, if the binary decision variable is commited. If the binary decision variable is commited, the fuel consumption must in return be higher than the minimum load. The fuel consumption used for CHP production and for bypass-mode can never exceed the maximum fuel capacity of the CHP. At last, if the CHP was turned off in the last hour, a start of the CHP must happen to turn it on.

$$CHP^{fuel}_{s,t} \leq CHP^{on}_{s,t}, \qquad \forall s \in S, t \in T \tag{3.33}$$

$$CHP^{fuel}_{s,t} \geq CHP^{on}_{s,t} \cdot \underline{CHP}^{fuel}, \qquad \forall s \in S, t \in T \tag{3.34}$$

$$CHP^{prod}_{s,t} + CHP^{bypass}_{s,t} = CHP^{fuel}_{s,t}, \qquad \forall s \in S, t \in T \tag{3.35}$$

$$CHP^{start}_{s,t} \geq CHP^{on}_{s,t} - CHP^{on}_{s,t-1}, \quad \forall s \in S, t \in T \tag{3.36}$$

The following constraints define the initial condition of the CHP and the thermal storage, using the value of the last hour. Furthermore, the thermal storage content of the last hour in the planning horizon must be equal to the thermal storage content in the first hour.

$$CHP^{on}_{s,0} = CHP^{on}_{initial} \quad \forall s \in S \tag{3.37}$$

$$TS_{s,0} = TS_{initial} \qquad \forall s \in S \tag{3.38}$$

$$TS_{s,|T|} = TS_{initial} \qquad \forall s \in S \tag{3.39}$$

The following constraints couple the scenarios in such a way, that the bids on the day-ahead market form a monotonic curve. To clarify this, if the spot price in scenario A is lower than the spot price in scenario B, then the consumption of electricity in scenario A must be lower or equal to the consumption in scenario B. If the spot price is identical between scenario A and B, then the consumption of electricity must be the same in both scenarios.

$$spot^{trade}_{s,t} \geq spot^{trade}_{s',t} : \quad spot^{price}_{s,t} < spot^{price}_{s',t}, \quad \forall (s,s') \in S, t \in T \tag{3.40}$$

$$spot^{trade}_{s,t} = spot^{trade}_{s',t} : \quad spot^{price}_{s,t} = spot^{price}_{s',t}, \quad \forall (s,s') \in S, t \in T \tag{3.41}$$

The same principles as for the traded electricity on the day-ahead markets is valid for the trading on the regulating market.

$$reg^{up}_{s,t} \geq reg^{up}_{s',t} : \quad up^{price}_{s,t} > up^{price}_{s',t}, \qquad \forall (s,s') \in S, t \in T \tag{3.42}$$

$$reg^{up}_{s,t} = reg^{up}_{s',t} : \quad up^{price}_{s,t} = up^{price}_{s',t}, \qquad \forall (s,s') \in S, t \in T \tag{3.43}$$

$$reg^{down}_{s,t} \geq reg^{down}_{s',t} : \quad down^{price}_{s,t} < down^{price}_{s',t}, \quad \forall (s,s') \in S, t \in T \tag{3.44}$$

$$reg^{down}_{s,t} = reg^{down}_{s',t} : \quad down^{price}_{s,t} = down^{price}_{s',t}, \quad \forall (s,s') \in S, t \in T \tag{3.45}$$

The following constraint defines flow of heat. The energy content of the thermal storage must be equal to the energy content in the last hour minus the demand, plus the heat production on the energy conversion units.

$$\begin{aligned}
TS_{s,t} \quad = \quad & TS_{s,t-1} \\
& - h(ambient_{s,t}) \\
& + WCB_{s,t} \cdot \overline{WCB}_{heat} \\
& + EB_{s,t} \cdot \overline{EB}_{heat} \\
& + HP_{s,t} \cdot \overline{HP}_{power} \cdot j(ambient_{s,t}) \\
& + \overline{CHP}^{base}_{heat} \\
& + CHP^{prod}_{s,t} \cdot \overline{CHP}^{prod}_{heat} \\
& + CHP^{bypass}_{s,t} \cdot \overline{CHP}^{bypass}_{heat}, \quad \forall s \in S, t \in T
\end{aligned} \tag{3.46}$$

The following constraint defines the physical flow of electricity. The difference between the import and export of electricity must be equal to the sum of all consumption of electricity minus the sum of all produciton of electricity.

$$\begin{aligned}
grid^{import}_{s,t} - grid^{export}_{s,t} \quad = \quad & HP_{s,t} \cdot \overline{HP}_{power} \\
& + EB_{s,t} \cdot \overline{EB}_{power} \\
& - WT_{s,t} \cdot \overline{WT}_{power} \cdot f(wind_{s,t}) \\
& - \overline{PV}_{power} \cdot g(irr_{s,t}, ambient_{s,t}) \\
& - CHP^{prod}_{s,t} \cdot \overline{CHP}^{prod}_{power}, \quad \forall s \in S, t \in T
\end{aligned} \tag{3.47}$$

The following constraint defines that the difference between the import and export electricity must be equal to the sum of the traded amount of electricity and the sum of the imbalances.

$$\begin{aligned}
grid^{import}_{s,t} - grid^{export}_{s,t} \quad = \quad & spot^{trade}_{s,t} \\
& + imbalance^{surplus}_{s,t} \\
& - imbalance^{deficit}_{s,t} \\
& + reg^{down}_{s,t} \\
& - reg^{up}_{s,t}, \quad \forall s \in S, t \in T
\end{aligned} \tag{3.48}$$

Third stage MILP only
When there are multiple scenarios in the MILP, it is likely that two different scenarios will have two different optimal production plans for the coming planning horizon. However, in the third stage, a decision on the optimal unit commitment across all scenarios must be taken for the coming hour. The decision variables for the coming hour must therefore be identical across all scenarios.

$$TS_{s,1} = TS_{s',1}, \quad \forall (s,s') \in S \tag{3.49}$$

$$HP_{s,1} = HP_{s',1}, \quad \forall (s,s') \in S \tag{3.50}$$

$$WCB_{s,1} = WCB_{s',1}, \quad \forall (s,s') \in S \tag{3.51}$$

$$EB_{s,1} = EB_{s',1}, \quad \forall (s,s') \in S \tag{3.52}$$

$$WT_{s,1} = WT_{s',1}, \quad \forall (s,s') \in S \tag{3.53}$$

$$CHP^{on}_{s,1} = CHP^{on}_{s',1}, \quad \forall (s,s') \in S \tag{3.54}$$

$$CHP^{start}_{s,1} = CHP^{start}_{s',1}, \quad \forall (s,s') \in S \tag{3.55}$$

$$CHP^{fuel}_{s,1} = CHP^{fuel}_{s',1}, \quad \forall (s,s') \in S \tag{3.56}$$

$$CHP^{prod}_{s,1} = CHP^{prod}_{s',1}, \quad \forall (s,s') \in S \tag{3.57}$$

$$CHP^{bypass}_{s,1} = CHP^{bypass}_{s',1}, \quad \forall (s,s') \in S \tag{3.58}$$

$$CHP^{prod}_{s,1} = CHP^{prod}_{s',1}, \quad \forall (s,s') \in S \tag{3.59}$$

$$grid^{import}_{s,1} = grid^{import}_{s',1}, \quad \forall (s,s') \in S \tag{3.60}$$

$$grid^{export}_{s,1} = grid^{export}_{s',1}, \quad \forall (s,s') \in S \tag{3.61}$$

$$imbalance^{deficit}_{s,1} = imbalance^{deficit}_{s',1}, \quad \forall (s,s') \in S \tag{3.62}$$

$$imbalance^{surplus}_{s,1} = imbalance^{surplus}_{s',1}, \quad \forall (s,s') \in S \tag{3.63}$$

3.2.7 Economic data

The following constant costs are used in the MILP as derived from the energyPRO-model from Assens District Heating. These costs are also in concordance with data from [51].

- 216 DKK/MWh-heat produced on the woodchip boilers for O&M
- 15 DKK/MWh-heat produced on the heat pump for O&M
- 5 DKK/MWh-heat produced on the electric boiler for O&M
- 10 DKK/MWh-e produced on the wind turbine for O&M
- 167.32 DKK/MWh-fuel consumed in the CHP for woodchips and O&M
- 3.3 DKK/MWh-e produced on the CHP for oil costs
- 167.1 DKK/MWh-e imported electricity for tariffs and taxes

3.2.8 Choice of solver

The mixed-integer linear programs have been programmed in Python and solved using CPLEX, as this is one of the most competitive commercial solvers available [52]. The mixed-integer linear programs with just a single scenario such as for the heat unit replacement bidding method have been solved to global optimum by setting the tolerance gap to 0%. The tolerance gap specifies how close the found solution needs to be to a theoretical best solution before the solver stops the optimization. For the mixed-integer linear programs with multiple scenarios, it has been necessary to increase the tolerance gap to 1% to retrieve a solution within on average 2 minutes per timestep in the simulation period.

3.3 Scenario generation

3.3.1 Generation of spot prices and weather data

To model the bidding methods, it is necessary to have prognoses for the spot price, aggregated solar irradiance, ambient temperature, and wind speed. It is crucial that these forecasts contain uncertainties and errors that would reproduce a real-life context of a unit commitment problem under uncertainty. However, it has been impossible to collect such prognoses, as they are sold as commercial products. Therefore, a novel method for generating forecasts has been developed in this project. The approach uses a combination of a Markov Chain and Monte Carlo simulation to generate time series in hourly steps, as this is an often used method for forecasting time series [53]. A Markov model is a set of states, in which each has a defined probability of switching to each other state. This can be applied to time series forecasting by using the last known value as a state, for example the spot price from 23:00 to 24:00, and drawing a random new state for the next hour. With process is continued until a state has been found for each timestep in the planning horizon. The same method with slight variations is used to generate scenarios for the spot price, aggregated solar irradiance, ambient temperature, and wind speed. The following explains the procedure for generating spot price scenarios.

First, a transition matrix is generated for each hour of the day, to capture daily variations in the spot price. The transition matrix contains the probabilities of transitioning from one state to another. The transition matrices are trained on data of real spot prices from 2018 to 2020. Multiple years are chosen such that outliers play a smaller role, while data from before 2018 is excluded, such that the matrices do not inherit properties of a market coupling in an energy system with significantly less renewable energy than in 2020. Note that the simulation period of October 1st to October 29th, 2020, is included in the training data, although it is mixed with a large amount of other data. To generate the transition matrices, the real spot prices are binned into 100 price ranges, which constitute the state of the spot price in that hour, relative to all the same hours in the training data. The data is binned such that each state is a percentile. The 24 hourly 100×100 transition matrices are initialized with zeros in all entries. Starting from 1st of January 2018, the percentile and therefore state of the electricity price in that hour and the coming hour is then found. If the electricity price for example was in the 55th percentile and the coming hour was in the 57th percentile, then the entry in row 55 and column 57 in the transition matrix for hours 00:00 – 01:00 is incremented by one. This procedure is followed for all 3 years of training data, whereafter each entry is divided by the sum of the row it belongs to. Some of the resulting transition matrices are depicted in Figure 3.5.

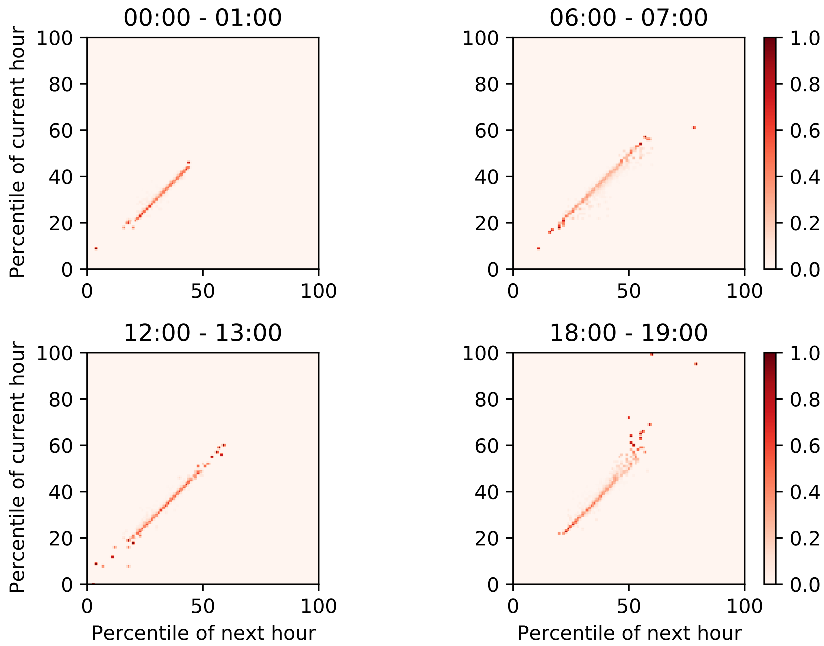

Figure 3.5. Transition matrices for the spot price for four selected hours of the day

As it can be seen in Figure 3.5, the transition matrices have a very diagonal structure, meaning that the electricity price in the next hour is very likely to be close to the electricity price in the previous hour. Each of the 24 transition matrices have a unique structure, which captures the daily variations in the electricity price. In the transition matrix for 18:00 – 19:00 it can for example see how the data is skewed from the diagonal structure, such that a state with a high percentile in that hour has a tendency of leading to a state with a lower percentile in the following hour.

The transition matrices are used to generate scenarios using Monte Carlo simulation on the Markov Chain, by iteratively generating a new random variable in the time series, using the percentile in the preceding hour as the lookup row and the entries of the columns in that row as the probability of generating a new value with the corresponding percentile. When a Markov Chain of percentiles have been generated for the entire planing horizon, the percentiles are converted back into actual electricity prices, by drawing a uniformly distributed random value from that bin. The procedure is repeated for each scenario. To generate the single forecast to be used for the single-scenario bidding methods such as the heat unit replacement bidding method, the mean of all the generated scenarios is used for each time step. The resulting time series of the forecasting method can be seen in Figure 3.6.

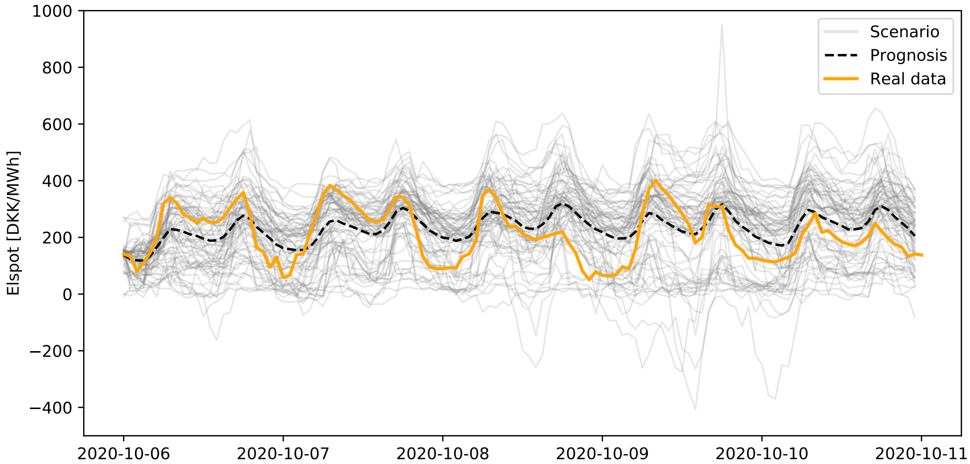

Figure 3.6. Generated scenarios and the single prognosis for the spot price compared to the real spot price in the same period

As it can be seen in Figure 3.6, the developed forecasting method is able to produce forecasts that express many of the characteristics of the actual spot price. Low spot prices, for example, show a tendency to linger around a spot price of 0 DKK/MWh-e, while only a few scenarios contain extreme values below 0 DKK/MWh-e. It can also be seen how the forecasts capture the daily trends in the electricity price with a peak in the morning and a peak in the afternoon. Finally, it can be seen that using the mean of the generated scenarios for the single prognosis results in a good approximation of the real spot data.

The picture in Figure 3.6 only shows the generated scenarios for one time step and the 5 days ahead, constituting the planning horizon. All the scenarios originate from the same common last known value of the spot price. However, as time is incremented in the model, new scenarios and a new prognosis is generated. In other words, the scenarios and the prognosis are dynamically being updated as the planning horizon is shifted, and new data is revealed to the model.

The same procedure as for the spot price is used to generate scenarios and the single prognosis for aggregated irradiance, ambient temperature, and wind speed. However, these weather data are assumed to be less uncertain than the spot prices, and therefore a small change is made to the procedure. This change involves revealing a little information about the real values of the future, and the method for generating weather scenarios is therefore strictly speaking no longer a forecast. The change consists of generating n random values instead of just one random value in the Monte Carlo simulation. It is then revealed which one of the n random values or rather states, that is closest to the state of the real value, and this value is chosen. The approach is therefore still stochastic, but the scenarios will have a smaller probability of drifting away from the actual value, while this value is still unknown to the model. The number of n random values to generate in each time step diminishes linearly as the simulation moves further away from the last known value, to reflect that uncertainty increases over time. In the first timestep of the planning horizon, n, is set to 4, while n linearly decreases to 1 at the last timestep in the planning horizon.

One final change is also made in the procedure for generating aggregated solar irradiance. As the sun's movement across the sky is vastly different throughout the year, the training data is limited to the 4 weeks in October, that the bidding methods are simulated in. To compensate for this reduction in the training data, the transition matrices are trained on data from 2015 to 2020 instead. The resulting generated scenarios for all the types of data can be seen in Figure 3.7 for a specific starting point. If time is incremented by one hour, the scenarios would look slightly different, as the value of the first timestep in the previous planning horizon is revealed, while the entire planning period is shifted one hour.

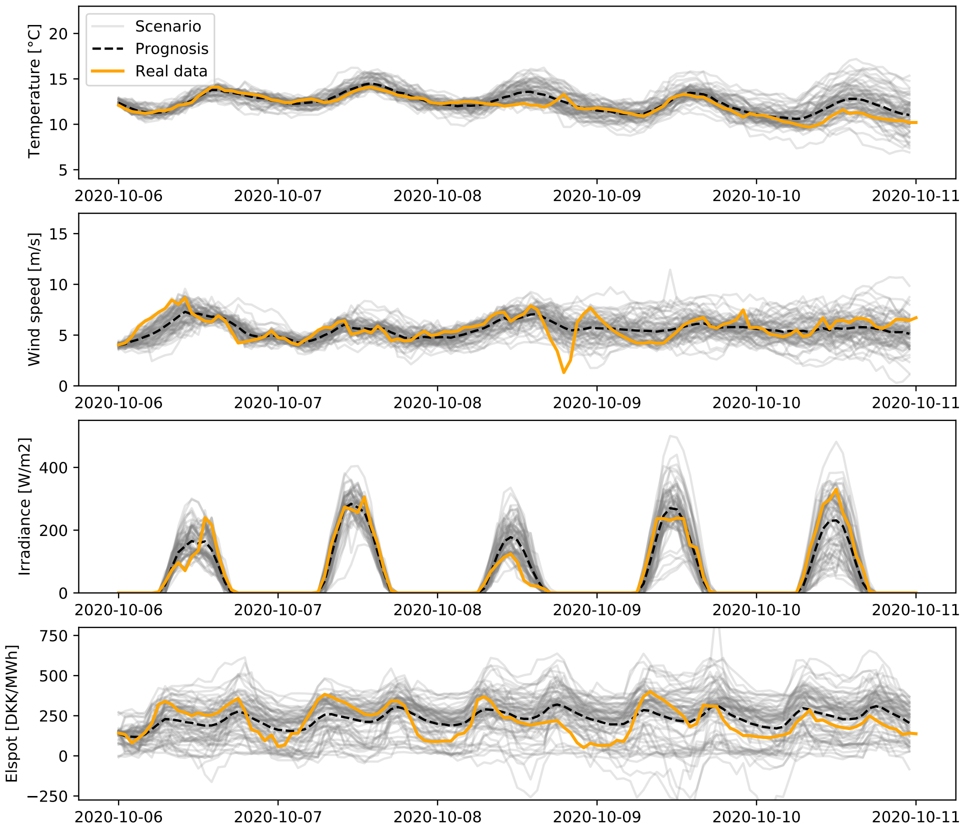

Figure 3.7. Generated scenarios and the single prognosis for all four types of data compared to the real values in the same period

As it can be seen in Figure 3.7, the developed method is able to produce scenarios for all 4 types of data, which both resembles the real data, while deviating enough to capture the uncertainties in the daily operational planning of the district heating plant. The vast majority of the real data lies within the upper and lower bounds of the scenarios, and the single prognosis is an accurate forecast.

3.3.2 Generation of regulating prices

The regulating price scenarios are not generated as time series but as scenarios for the coming hour only. There is a relationship between the spot price and the regulating price, as it can be seen in Figure 3.8, showing all up and down regulation prices for the year of 2020 in DK1.

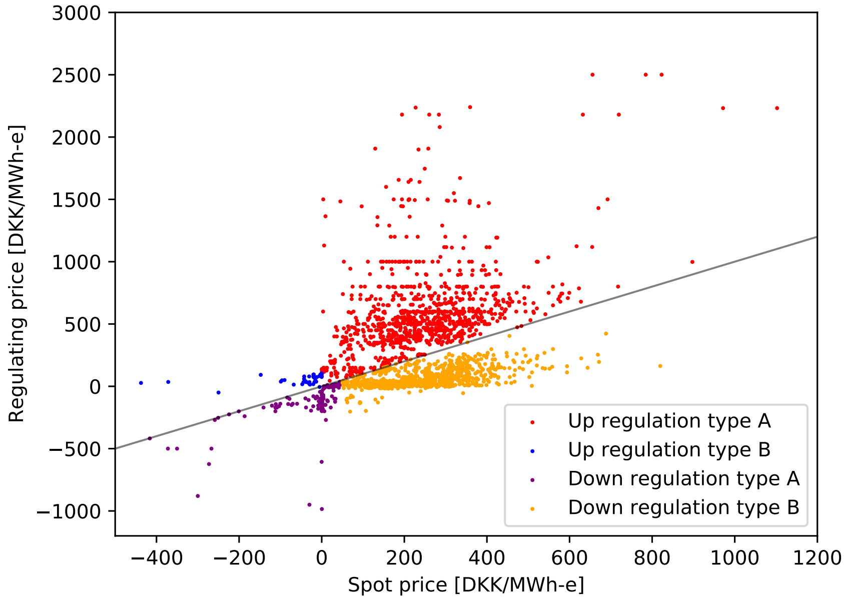

Figure 3.8. The relation between the regulating price and the spot price in 2020

In Figure 3.8, all the dots below the line, are down regulation prices, while all the dots above the line, are up regulation prices. Several tendencies can be seen in the regulating prices. In hours of up regulation, the up regulation price is very spread if the spot price is greater than 0. However, once the spot price falls below 0, the up regulating price keeps lingering around 0. For the hours with down regulation, the down regulating price tends to stay between 0 and the spot price. However, some extreme values are found with negative down regulating prices, especially when the spot price is also negative or near 0 DKK/MWh-e. While it is difficult to fit a single model to express the relation between the spot price and the regulating prices, these observations can be used to divide the problem into sub-problems. As the colors indicate in figure 3.8, the regulating prices are divided into 4 types:

- Up regulation type A, where the spot price is greater or equal to 0 DKK/MWh-e. The difference between the spot price and the up regulation price can be described as a logarithmic function with a normally distributed error term.

- Up regulation type B, where the spot price is less than 0 DKK/MWh-e. The up regulation price can be modelled with a normal distribution.

- Down-regulation type A, where the spot price is less than 50 DKK/MWh-e. The relation between the spot price and down regulation price can be described as a logarithmic function with a normally distributed error term.

- Down-regulation type B, where the spot price is greater or equal to 0 DKK/MWh-e. The down regulation price can be described as a linear function of the spot price with a normally distributed error term, where randomly sampled negative prices are corrected to 0 DKK/MWh-e with a probability derived from the observations.

By combining these 4 approaches, the regulating price can be modelled as a stochastic function of the spot price for a given hour. In figure 3.9, the approach is tested against the real regulating prices for the entire year of 2020.

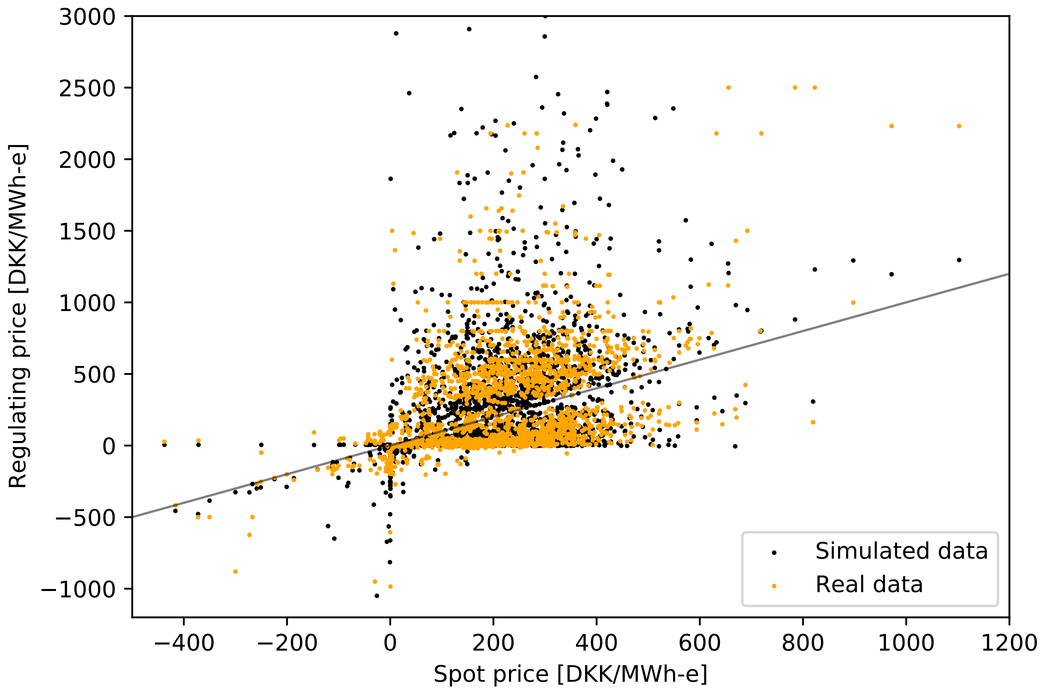

Figure 3.9. Simulated regulating prices compared to real regulating prices for the year of 2020

As it can be seen in Figure 3.9, simulated data resemble the real data well. The method is stochastic, allowing generation of multiple random regulating prices for a known spot price. The spot price for an operation hour is always known when the bids for the regulating market have to submitted. Scenarios for both down regulation and up regulation prices can therefore be simulated using this method.

3.4 Compared bidding methods

To understand how well a bidding method can lead to the optimal unit commitment for the district heating plant, it is necessary to have a reference to compare against. The reference is defined as the optimal unit commitment optimized across the entire simulation period at once, while having perfect knowledge about the future weather conditions and spot prices. Since the spot prices are known, this leads to a deterministic problem that can be easily solved. This reference is a lower bound for how well the district heating plant can be operated. However, if the district heating plant is also participating in the regulating market, it would not be meaningful to reveal the regulating prices in the reference, as this would lead to nonsensical and clearly unoptimal bids into the spot market, just to sell this traded energy in the regulating market right after. It would be the equivalent of knowing which lottery ticket to purchase. The first reference is therefore not allowed to participate in the regulating market.

Instead a second reference is made, which uses a rolling horizon with perfect knowledge about the spot prices and weather data for the coming 5 days. The regulating prices in this reference are revealed just before gate closure of the regulating market for the corresponding hour, and by knowing this price, a unit commitment problem is solved to find the optimal quantity of electricity to bid with. This is also a deterministic problem and would resemble the operation of a district heating plant with access to very good prognoses and no information about regulating prices, but an optimal approach for calculating the optimal bid into the regulating market.

The simplest way to solve the stochastic bidding problem is to place price-independent bids. This also results in a deterministic problem where only the optimal unit commitment has to be found, using the prognoses for the spot market and the weather data. Under the assumption that this unit commitment is in fact optimal, price-independent bids are then placed into the electricity markets, thus guaranteeing this expected optimal unit commitment. Price-independent bids can however lead to winning bids in hours of unanticipated extreme prices on the spot market. A method where the price-independent bids are bounded by an upper limit in the bidding price is therefore also analyzed. This upper limit is the electricity price at which it would be cheaper to produce heat on the woodchip boilers. For price-independent bidding methods, it is assumed that the regulating bids can be calculated by change of opportunity in the spot market, as it is done for the heat unit replacement bidding method.

The heat unit replacement bidding method is analyzed only for the simple case, as it is not possible to use the method for Assens District Heating considering their specific portfolio of units.

Finally, the approach based on scenario-generation and Sample Average Approximation is analyzed. For the simple case, 70 scenarios are generated for the spot prices and weather data for each rolling planning horizon in the model. For calculating the bids to be placed in the regulating market, 70 scenarios for down regulating prices and 70 scenarios for up regulation are also generated for each hour. For the full case of Assens District Heating, the amount of scenarios is reduced to 50. This proved to result in a slightly worse solution than using 70 scenarios, but was necessary to achieve a faster computation.

The analyzed references and methods in the analysis are named as follows:

- **Optimal** (reference)
  The optimal unit commitment problem on the entire simulation period with perfect knowledge about all prices and weather data, except the regulating market. No participation in the regulating market is allowed.

- **PF** (reference)
  The reference with a rolling horizon, where the spot prices and weather data is known with 100% accuracy (perfect forecasting) for the coming 5 days. Regulating prices are only known right before a regulating bid has to be submitted.

- **PI** (realistic bidding method)
  The bidding method consisting of placing price-independent bids only.

- **PI-L** (realistic bidding method)
  The bidding method consisting of placing price-independents bids with an upper limit on the price.

- **HURB** (realistic bidding method for the simple case only)
  The heat unit replacement bidding method.

- **SAA** (realistic bidding method)
  The bidding method based on scenario-generation and Sample Average Approximation to solve the stochastic unit commitment problem.

Chapter 4

Results for the simple case

4.1 Bidding in the day-ahead market only

The simple case is the hypothetical case of Assens District Heating, including only the woodchip boilers, electric heat pump and the thermal storage. The total operational expenses for the two references and the four analyzed bidding methods can be seen in Figure 4.1.

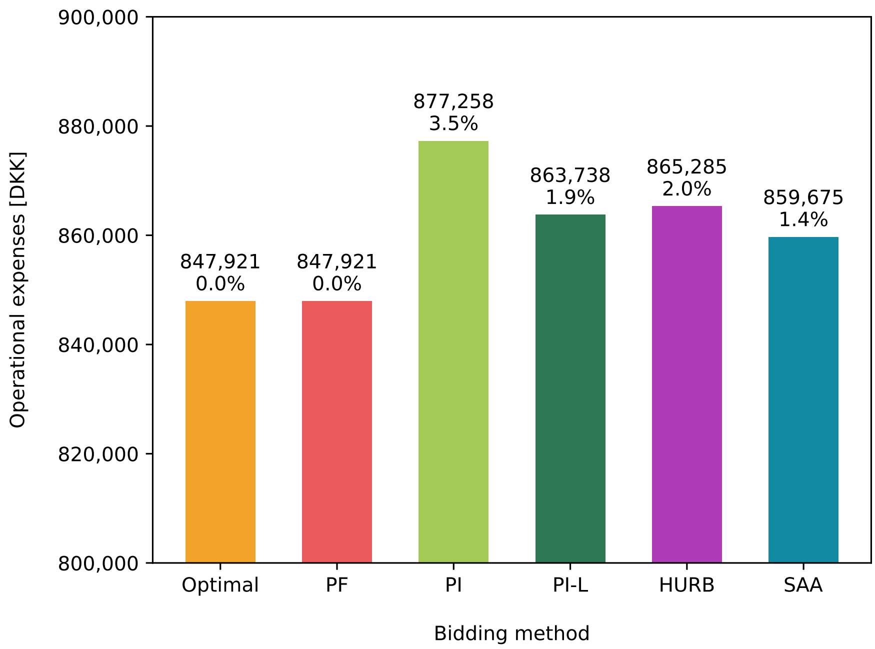

Figure 4.1. The total operational expenses over the analyzed simulation period from 1st of October to 29th of October. The percentage refers to the relative value between the corresponding bidding method and the optimal operation.

It is important to note, that the total operational expenses only include the costs that are included in the model. Some fixed costs, which remain the same no matter the operation, are not included in the model, and therefore also not in the operational expenses seen in Figure 4.1.

An important result that can be seen from Figure 4.1, is that there is no difference between the two references. Calculating the unit commitment problem at once and calculating it hour-by-hour with a 5 days rolling planning horizon leads to the exact same optimal operation. It verifies that a planning horizon of this length is sufficient for this case. It also reveals just how important good prognoses are.

Another notable result, is that price independent bidding with an upper limit performs equally well as the heat unit replacement bidding method. The heat unit replacement bidding method places substantially more bids in the day-ahead market than the price independent bidding method, as the heat unit replacement bidding method also places bids in hours it does not expect to win. However, this does not seem to lead to a more optimal operation. The small differences in operational expenses between the last three methods in Figure 4.1, does not lead to the conclusion that one bidding method is superior or inferior to another. Stochasticity also plays a role, as the optimal unit commitment from one method may lead to a lower operational expense by pure luck. However, it can be seen that Sample Average Approximation is a very competitive method for placing bids.

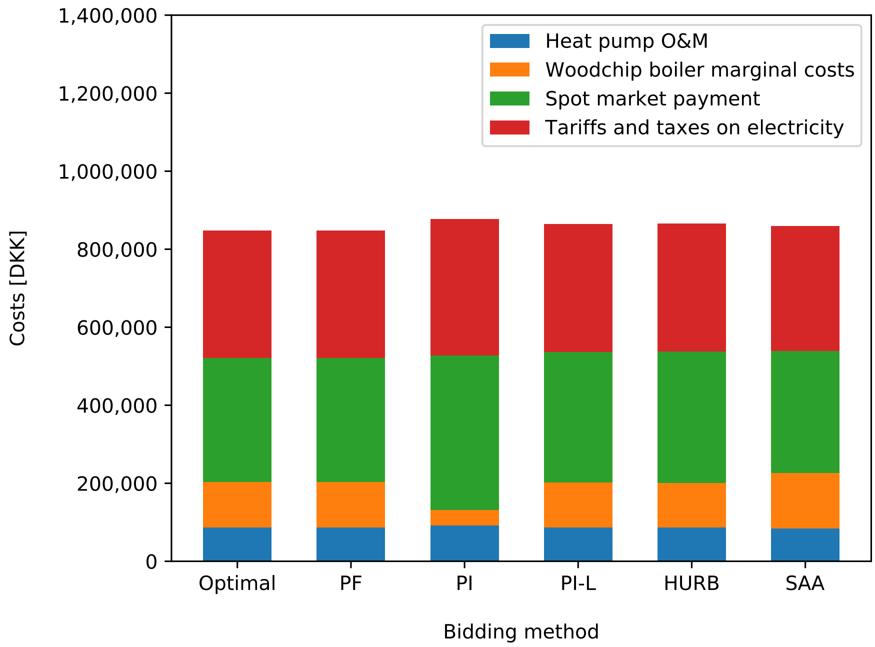

Figure 4.2. Total operational expenses based on their origin.

In Figure 4.2, the total operational expenses can be seen divided on their origin. The by far majority of all expenses are related to the purchase of electricity on the spot market, and the taxes and tariffs for importing electricity from the grid. A small proportion is related to the costs for producing heat on the woodchip boilers. These costs include variable O&M, taxes and fuel costs. As the costs of producing heat on the woodchip boiler is a constant, Figure 4.2 can he used to compare the amount of heat being produced on the woodchip boilers between the bidding methods. The approach based on Sample

Average Approximation produces a little more heat on the woodchip boilers than the heat unit replacement bidding method. The price-independent approach without an upper bidding limit produces substantially less heat on the woodchip boilers, as it wins every bid submitted, while the other methods only win bids when the spot price is below the bidding price. In Figure 4.3, the weighted average spot price of all the bids won can be seen, as well as the average size or quantity of the bids.

Figure 4.3. Weighted average spot price and average quantity of purchased electricity of all the won bids.

As it can be seen in Figure 4.3, the price-independent method without upper limits on the bidding price results in electricity being purchased at an averagely higher price. The approach based on Sample Average Approximation comes very close to purchasing the electricity at the optimal price. However, in the Sample Average Approximation method, the size of the bids are smaller. The average quantity should not be understood as the total electricity purchased on the day-ahead market, but the average quantity of electricity purchased for the hours with won bids only. The Sample Average Approximation method therefore places smaller bids, but at the optimal price. One of the reasons that the Sample Average Approximation method places smaller bids, is because it contains 70 scenarios with varying heat demands and COP. If the thermal storage is full, purchasing too much electricity on the spot market can lead to imbalances, as the electricity simply cannot be consumed. Some of the scenarios will have both a lower heat demand and a higher COP than the average scenario, due to higher ambient temperatures. To avoid imbalances, the Sample Average Approximation method therefore places slightly lower bids than the maximum electric capacity of the heat pump, to avoid imbalances in just a few of the scenarios. How this affects the deficit electricity consumption can be seen in Figure 4.4.

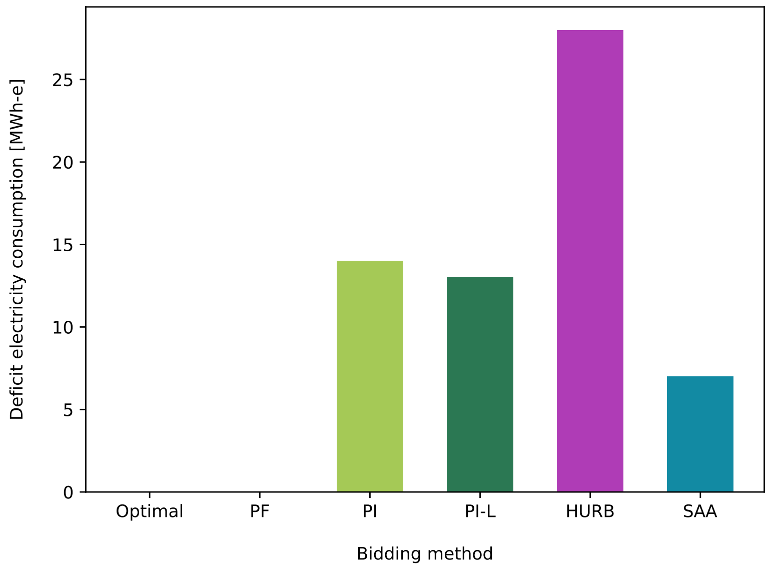

Figure 4.4. Imbalances of deficit electricity consumption, which occurs when more electricity was purchased than consumed.

The imbalances seen in Figure 4.4 lead to a refund of the purchased electricity. However, if the regulating price is lower than the spot price, the value of this refund is smaller than the expense of purchasing the electricity, leading to increased operational expenses. None of the bidding methods have surplus electricity consumption imbalances, as the woodchip boilers can always be dispatched, if too little electricity was purchased to supply the heat demand with the heat pump only.

The approach based on Sample Average Approximation results in bidding curves with up to the same number of steps as there are scenarios in the model. Although, most of the bidding curves contain only a few number of steps, as only some of the scenarios become the tipping points, where bids for additional consumption are submitted. The heat unit replacement bidding method also produces bidding curves with multiple steps. These bidding curves contain up to the same number of steps as there are heat-only units being replaced. In the simple case, three woodchip boilers are replaced. However, as these woodchip boilers have the same costs, the bidding curves only contain one bid. A comparison of the bidding curves between these two methods for four selected hours can be seen in Figure 4.5.

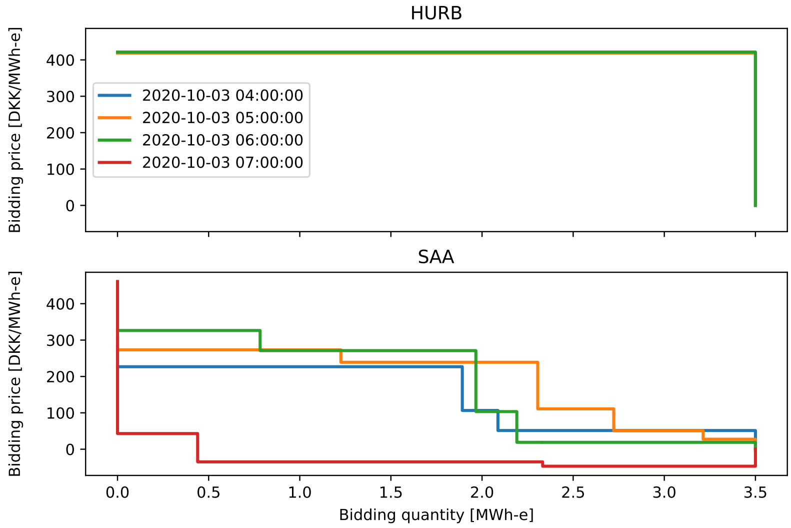

Figure 4.5. Bidding curves submitted for the heat unit replacement method and the approach using Sample Average Approximation for four selected hours in the simulation period.

In Figure 4.5, the heat unit replacement bidding method results in four identical and single bids with a quantity of 3.5 MW-e and a bidding price of approximately 400 DKK/MWh-e. This bidding price is the equilibrium at which the heat pump and the woodchip boilers are equally expensive to produce heat on. In the approach based on Sample Average Approximation on the other hand, multiple bids are submitted for each hour with different corresponding quantities and bidding prices. Most notably are the maximum bidding prices of these bids much lower. For the 3rd of October at 06:00:00, as the green line in Figure 4.5 depicts, the highest bid submitted is 0.8 MWh-e at a bidding price of 325 DKK/MWh-e. An additional 1.2 MWh-e is then submitted at a bidding price of 280 DKK/MWh-e. Only if the price for electricity is close to 0 DKK/MWh-e is the highest bid of 3.5 MWh-e won. In Figure 4.6, the bidding curves are visualized in a different way for a longer time period. The height of the bars represent the bidding quantity and the color of the bars represent the bidding price. A bidding price of 0 DKK/MWh-e or lower corresponds to a dark red color, while a bidding price of 400 DKK/MWh-e or higher corresponds to a dark green color. Bidding prices in between these values are depicted with a color gradient.

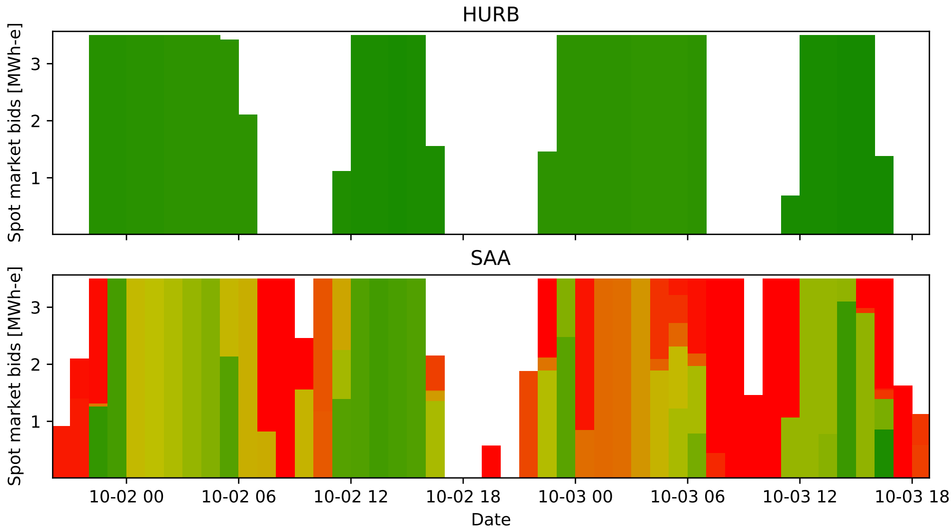

Figure 4.6. Bidding curves submitted for the heat unit replacement method and the approach using Sample Average Approximation for a selected time period of 42 hours. The bidding price is visualized with a color gradient, with dark green depicting a bidding price at 400 DKK/MWh-e or higher, and dark red depicting a bidding price at 0 DKK/MWh-e or lower.

As it can be seen in Figure 4.6, the method based on Sample Average Approximation places bids in far more hours than the the heat unit replacement method does, while it at the same is time more reluctant to place high bidding prices. This results more load hours on the heat pump, while being operated at a lower capacity, which explains the trends seen in Figure 4.3. The advantage of the Sample Average Approximation approach is thus clear. It places many bids around 0 DKK/MWh-e, which are not expected to be won. But if these bids are won because the market coupling in the day-ahead market takes an unexpected turn, they result in very cheap production of heat. The heat unit replacement bidding method is not capable of submitting such extreme and unlikely bids and instead focuses on placing fewer, larger and more conservative bids.

In Figure 4.7, actual unit commitment of three of the methods is compared against the realized spot prices. In the reference with perfect forecasting, the real spot price was used to plan the unit commitment, and it can be seen how production on the heat pump is avoided in hours where the electricity price peaks. In the shown time period, no production on the woodchip boiler occured. It can be seen how the bidding curves submitted in the approach based on Sample Average Approximation result in a unit commitment that closely resembles the optimal unit commitment. However, the bids submitted with the heat unit replacement bidding method result in a few deviations from the optimal unit commitment. On 7th of October at noon, a local minimum in the spot price of around 250 DKK/MWh-e occurs before the price increases again to around 350 DKK/MWh-e. The spot prognosis for this time period fails to anticipate this, and no bids are submitted, while bids are submitted in the adjacent hours. The spot price might be well below the point, where it is cheaper to operate the woodchip boiler, but the failure to place multiple bids in these hours results in electricity being purchased at a price almost 100 DKK/MWh-e higher than the optimal unit commitment. Another example is October 9th, where a peak of 400 DKK/MWh-e occurs in the morning. Many bids are won here for a price between 300 and 400 DKK/MWh-e, while the failure to place enough bids results in not operating the heat pump a few hours later, where the spot price is around 200 DKK/MWh-e.

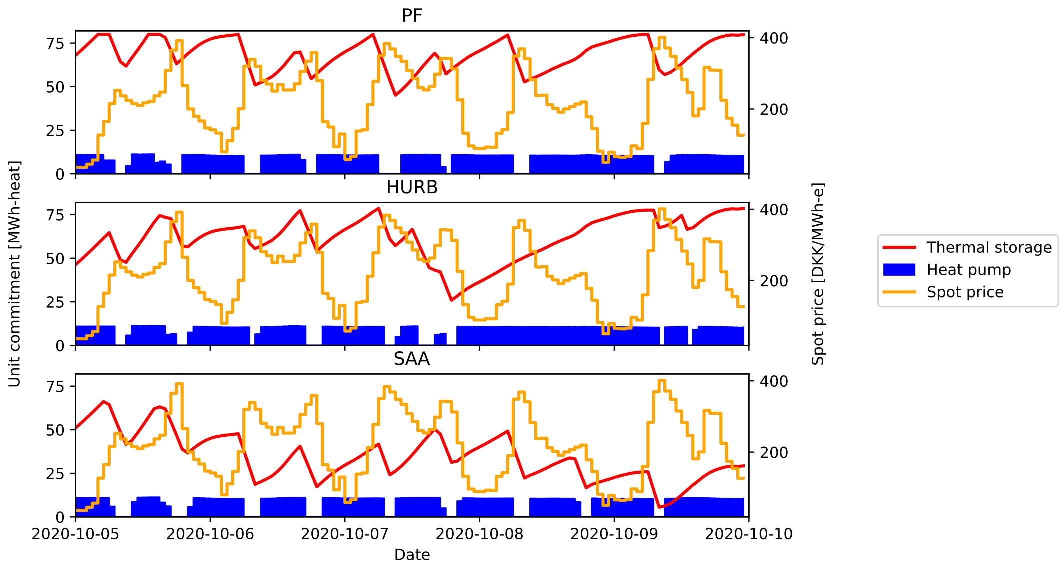

Figure 4.7. The unit commitment compared to the spot price for a selected period of time in the simulation.

4.2 Including the regulating bids

The regulating bids are not calculated for the optimal reference as this would be nonsensical, but the optimal operation without participating in the regulating market is included in the analysis for comparison. In Figure 4.8, the total operational expenses are shown, when the district heating plant can bid in the regulating market as well.

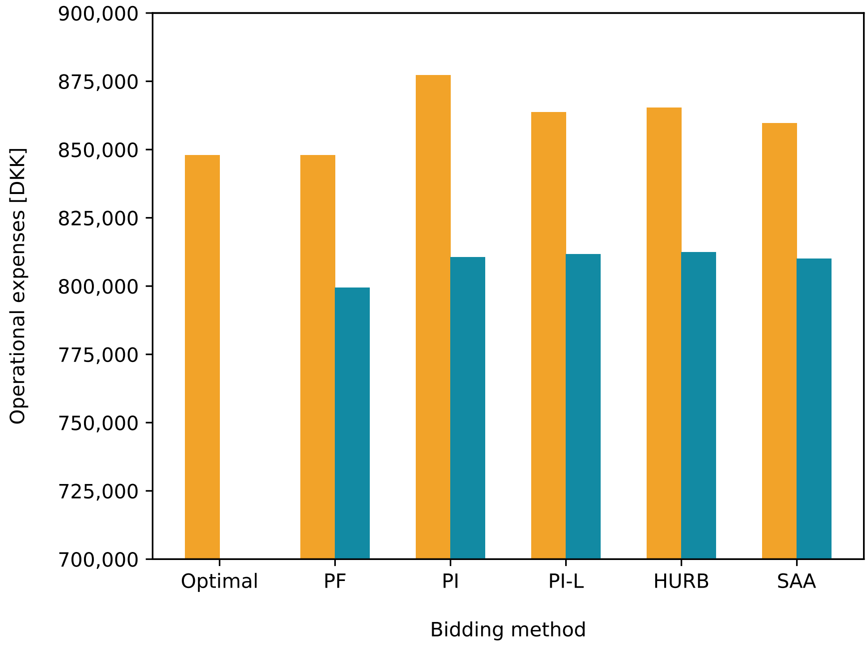

Figure 4.8. The total operational expenses over the analyzed simulation period from 1st of October to 29th of October. The orange bars to the left are the operational expenses without participating in the regulating market, and the green bars to the right are the operational expenses while participating in the regulating market as well.

As it can be seen in Figure 4.8, all of the bidding methods perform very similar when bids can be placed in the regulating market as well. None of the methods perform as good as the reference with perfect forecasting, and the method based on Sample Average Approximation performs slightly better than the other methods. It seems that poorly submitted bids in the day-ahead market can be made up by placing bids in the regulating market afterwards. This tendency can also be seen in Table 4.2.

	PK	PI	PI-L	HURB	SAA
Spot market [MWh-e]	1,949	2,120	1,974	1,976	1,914
Down [MWh-e]	38	2	35	32	39
Up [MWh-e]	191	257	211	211	200
Spot market [DKK]	321,155	405,362	341,604	342,292	318,154
Down [DKK]	7959	352	7553	6615	7891
Up [DKK]	-106,863	-150,660	-116,999	-116,999	-110,578

Table 4.1. Traded electricity on the different electricity markets as well as the total expenses for each of the markets. A negative expense is the same as an income.

In Table 4.2, it can be seen how a significantly higher amount of electricity is traded on the day-ahead market for the price-independent method without an upper limit on the bidding price. However, the amount of revenue made from trading on the up regulating market is correspondingly higher as well. This trend is occuring in all the data. A down regulation is the act of purchasing electricity cheaper or equal to the spot price, which requires an unscheduled start of the heat pump. An up regulation is the act of selling electricity more expensive than it was purchased for, which requires shutting down scheduled heat pump operation. The revenue earned on the up regulating market includes a refund for the electricity purchased on the spot market, which is why this value seems excessive. By dividing the revenue from the up regulating market with the amount of up regulation activated, up regulating bids are won with a price of approximately 500 - 600 DKK/MWh-e. Down regulating bids on the other hand, are won with a price of approximately 200 DKK/MWh-e. This corresponds well with the opportunity cost of producing heat on the woodchip boiler instead. The ability of the woodchip boiler to replace heat pump production is what allows the significant amount of up regulation, as it can be seen in Figure 4.9.

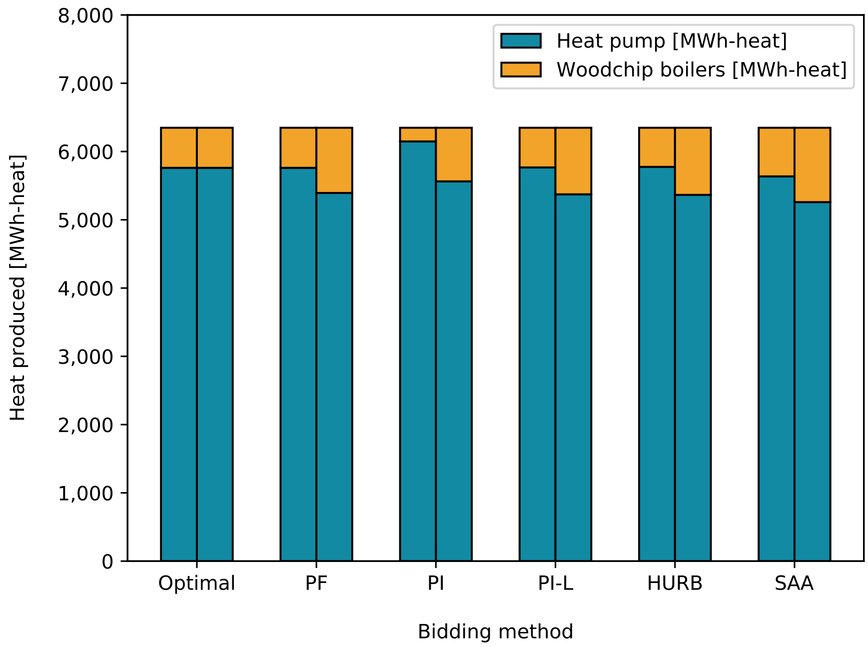

Figure 4.9. Heat produced on the heat pump and woodchip boilers. The left bar shows the heat produced without participating in the regulating market, and the right bar shows the heat produced with participation in the regulating market.

It has now been shown that the approach based on scenario generation and Sample Average Approximation is a very competitive bidding method, both compared to the optimal unit commitment, and to the state-of-the-art heat unit replacement bidding method. It performs well when submitting bids to both the day-ahead market and the regulating market. However, on the contrary to the heat unit replacement bidding method, the approach based on Sample Average Approximation can be applied to the case of Assens District Heating.

Chapter 5

Results for the full case

5.1 Bidding in the day-ahead market only

For the analysis of the full case of Assens District Heating, the heat unit replacement bidding method has not been included, as it is unable to calculate a meaningful operation. The price independent method without an upper limit is also omitted. In Figure 5.1, the total expenses of the two bidding methods are compared to the optimal operation of the district heating plant in the two references.

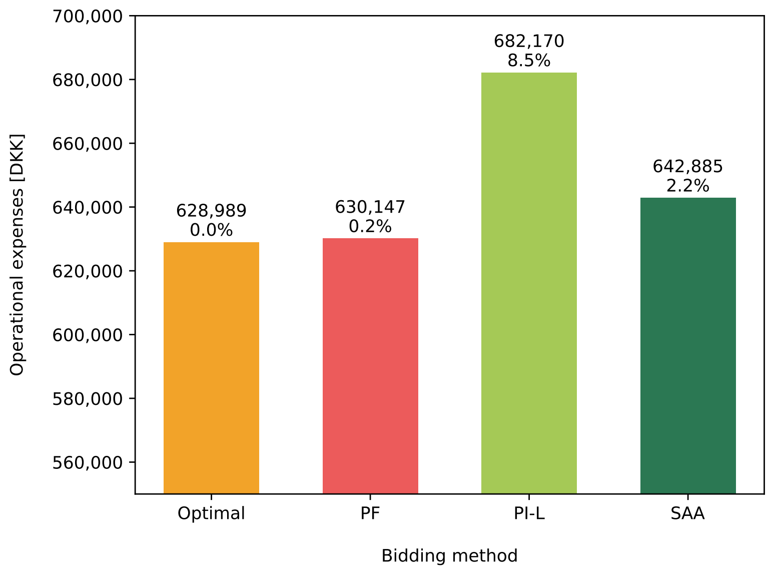

Figure 5.1. The total operational expenses over the analyzed simulation period from 1st of October to 29th of October. The percentage refers to the relative value between the corresponding bidding method and the optimal operation.

As it can be seen in Figure 5.1, the approach using Sample Average Approximation is still able to come very close to the optimal operation, while this is no longer the case for the price independent method. It can furthermore be seen that applying a rolling planning horizon creates a difference between the reference with optimal unit commitment and the reference with a rolling planning horizon with perfect forecasting. In Figure 5.2, the heat production and electricity production of the energy conversion units can be seen.

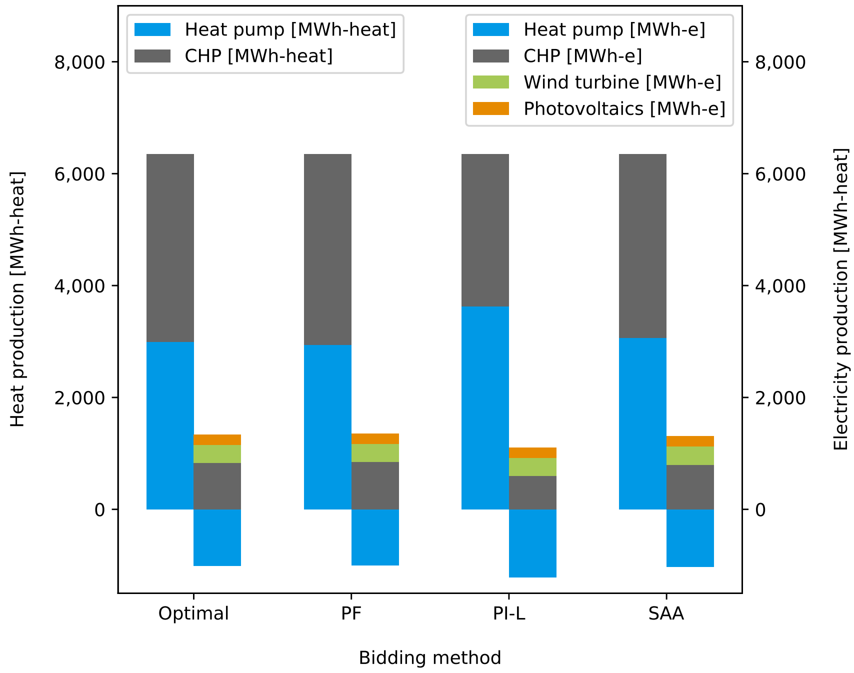

Figure 5.2. Heat production and electricity production of the energy conversion units at the district heating plant. A negative production is a consumption of electricity. The electric boiler and woodchip boilers are not shown, as they produced so small amounts that it cannot be visualized.

In Figure 5.2, it can be seen that the method based on Sample Average Approximation leads to the same total amount of produced energy on the different units as the optimal operation. The price-independent method, on the other hand, ends up producing substantially more heat on the heat pump and operating the CHP correspondingly less. It can also be seen how the wind turbines and photovoltaics contribute to a significant amount of the produced electricity. For the optimal operation, the perfect forecasting and the method based on Sample Average Approximation, slightly more electricity is sold than purchased. For the price-independent method, significantly less electricity is sold than purchased.

In Figure 5.3, it can be seen why this occurs. For the optimal operation, electricity is generally only sold once the spot price is above 300 DKK/MWh-e, and electricity is only purchased once the spot price is below 150 DKK/MWh-e. This trend is similar for the approach based on Sample Average Approximation. However, for the price-independent bidding method, large quantities of electricity are sometimes sold for low spot prices and large quantities are correspondingly purchased for spot prices up towards 400 DKK/MWh-e. While a spot price of 400 DKK/MWh-e still allows cheaper heat production on the heat pump than on the woodchip boiler, it is clearly not feasible to submit such a high bid.

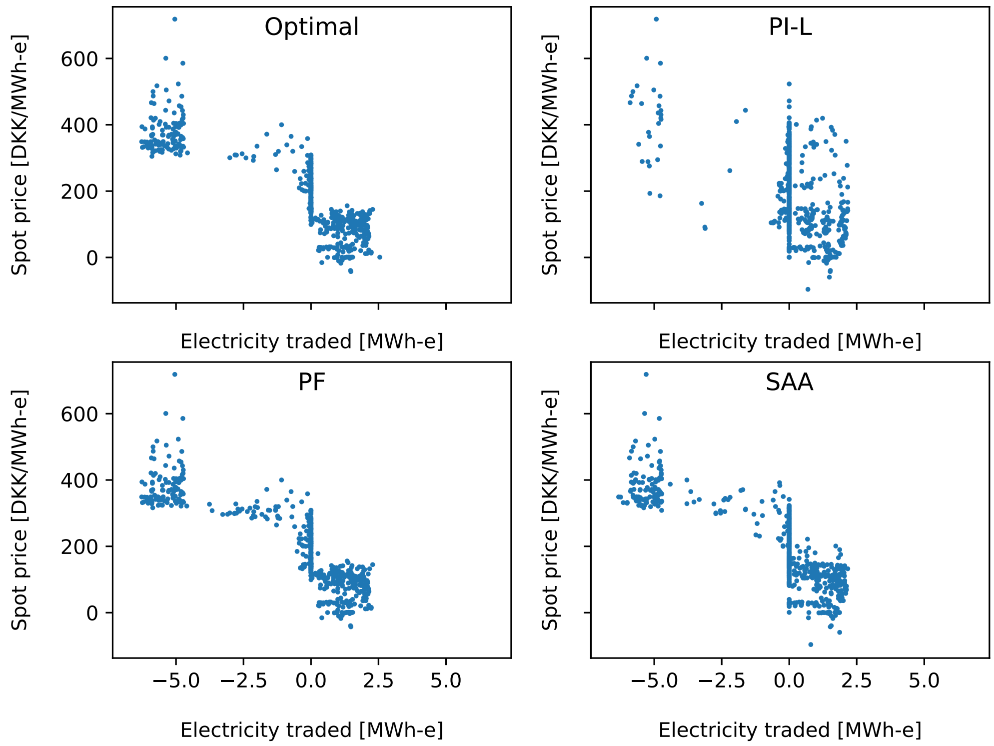

Figure 5.3. Won bids traded on the spot market plotted against the realized spot price. A negative trade of electricity is a sale of electricity, and a positive trade of electricity is a purchase of electricity.

In Figure 5.4, the bidding curves are visualized for the method based on Sample Average Approximation. Several observations can be made from the figure. First of all, the large red spikes are bids submitted for the electric boiler, due to some scenarios in the model predicting extremely low spot prices. These bids are very rarely won, but the bids are still submitted because it would result in essentially free heat, if such a market coupling occured. The ability to place such bids is a significant strength of the Sample Average Approximation approach. However, as only 50 scenarios are included in model formulation, the chances of extremely low electricity prices occuring are not expressed in every timestep of the model. This could explain why large bids are only submitted for some hours. If the number of scenarios in the model was increased, it could be possible that such extreme bids are placed in every hour.

Second, bids for sale of electricity are rarely submitted during the night, where the spot price is typically lower than during the day. The reason for this can be explained with the cost incurred for starting the CHP. It is in other words often the case that none of the scenarios in the model predict high spot prices for enough consecutive hours to make starting the CHP feasible.

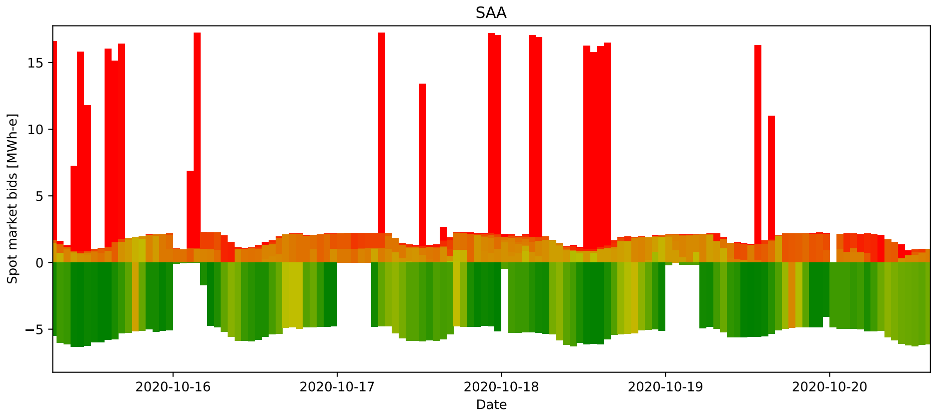

Figure 5.4. Bidding curves submitted for the approach using Sample Average Approximation for a selected time period. The bidding price is visualized with a color gradient, with dark green depicting a bidding price at 400 DKK/MWh-e or higher, and dark red depicting a bidding price at 0 DKK/MWh-e or lower.

Third, unlike in the simple case, the size of the largest bid varies a lot between each timestep. This is due to the electricity production from the wind turbines and photovoltaics varying throughout the day. The largest bids for purchase of electricity are determined by the remaining electricity capacity of the heat pump after using the private-wire operated electricity. For the bids for sale of electricity same trend happens, where the fluctuating renewable electricity is sold together with the production of electricity from the CHP. In Figure 5.5, an example of the bidding curve submitted is shown for four selected hours.

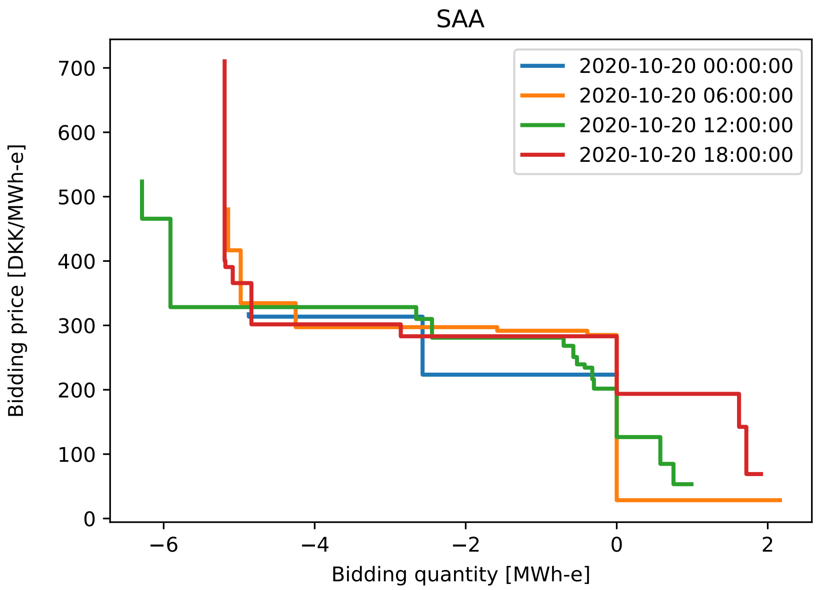

Figure 5.5. The bidding curves calculated by the approach using Sample Average Approximation for four selected hours. A negative bidding quantity is a bid for sale of electricity and a positive bidding quantity is a bid for purchase of electricity.

In Figure 5.5 it can be seen, that the largest bid submitted depends on the hour of the day. For the hour of 12:00, depicted by the green line, the largest submitted bid is 6.2 MWh-e. During the evening 6 hours later, depicted by the red line, the power production from the photovoltaics is significantly lower, and only bids for 5.2 MWh-e can be submitted. It can also be seen in Figure 5.5, how the tipping point for selling electricity occurs around 300 DKK/MWh-e, while the tipping point for purchasing electricity occurs below 200 DKK/MWh-e. If the spot price is somewhere in between these two points, the district heating plant neither sells or purchases electricity.

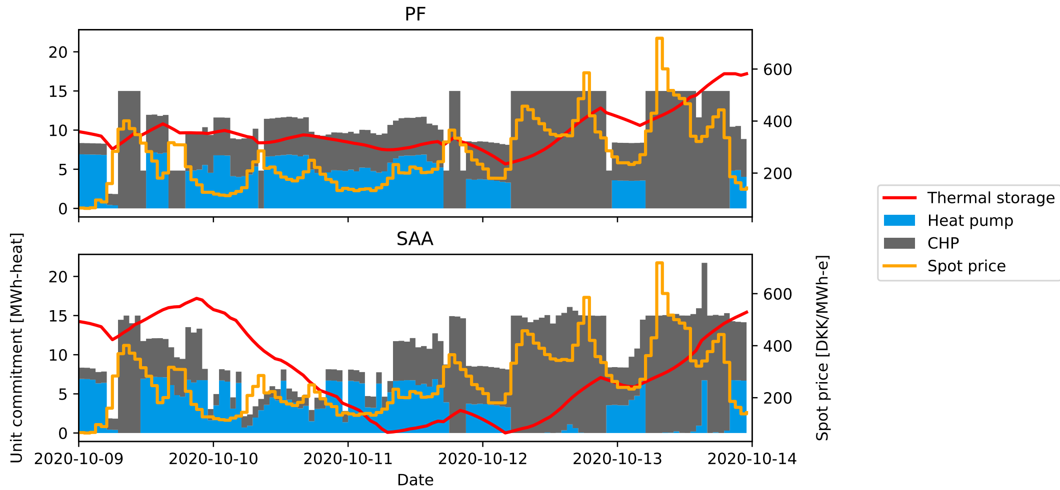

Figure 5.6. Unit commitment and the resulting heat production in selected hours.

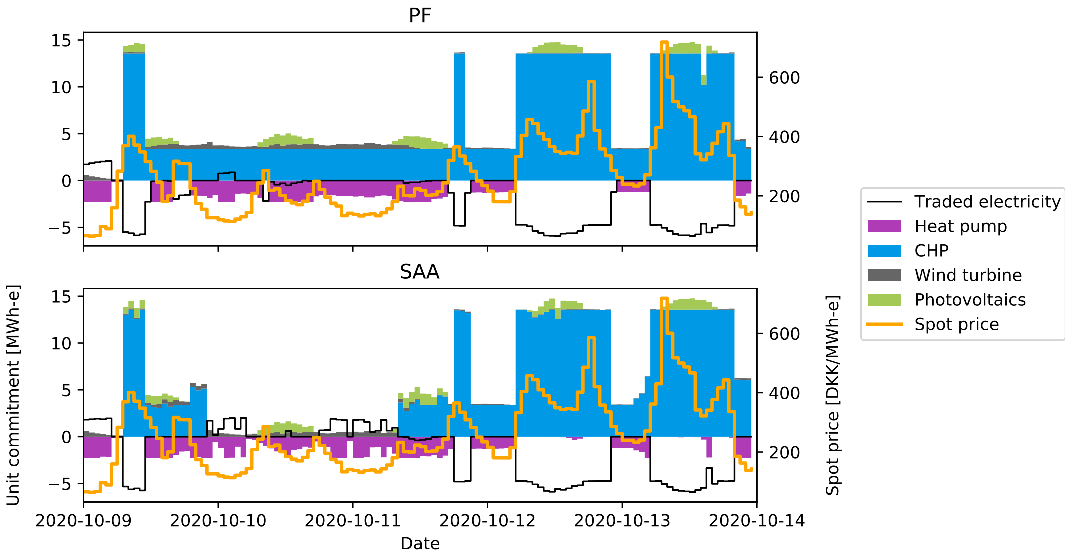

Figure 5.7. Unit commitment and the resulting electricity production and consumption in selected hours.

In Figure 5.6 and Figure 5.7, the unit commitment for the perfect forecasting reference and the method based on Sample Average Approximation can be seen for a selected time period. It can be seen how the CHP is succesfully being operated whenever the electricity price is high, and that low electricity prices between two peaks results in the electricity being consumed by the heat pump rather than shutting down the CHP. Electricity is generally only being purchased during the night when both the electricity price is low and the photovoltaics are not producing electricity.

5.2 Including the regulating bids

The regulating bids are not included for the price-independent method. This analysis therefore only compares the method based on Sample Average Approximation to the perfect forecasting reference. Most interestingly, the Sample Average Approximation leads to lower total operational expenses than the reference! This can be seen in Figure 5.8.

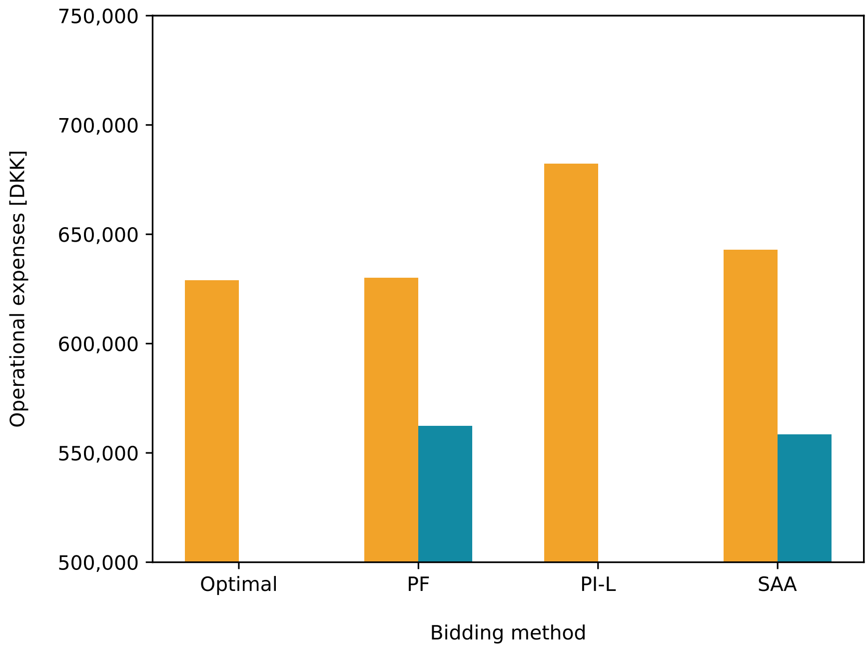

Figure 5.8. The total operational expenses for the different bidding methods when including the regulating market. The yellow bar to the left shows the results without trading on the regulating market.

For the reference with perfect forecasting, the total expenses amount to 562,355 DKK, while the same amount for the method using Sample Average Approximation is 558,318 DKK. While it may seem counter intuitive that the realistic bidding method outperforms the reference, it can be explained by coincidence. The perfect forecasting reference is only able to predict the next 5 days of spot prices and weather data, and it does not know the future regulating prices. Based on this, an optimal unit commitment is calculated. However, this might lead to a production plan that by chance happens to lead to less available capacity for bidding in the regulating market, than the unit commitment calculated using Sample Average Approximation. In other words, the slightly suboptimal unit commitment calculated by the approach based on Sample Average Approximation is allowing better participation in the regulating market, for which the prices and volumes were unknown for both the reference and the bidding method. If new scenarios were generated for the Sample Average Approximation and the calculations were repeated, a slightly different unit commitment plan could have led to operational expenses that were instead higher than the reference. This is the nature of stochastic unit commitment.

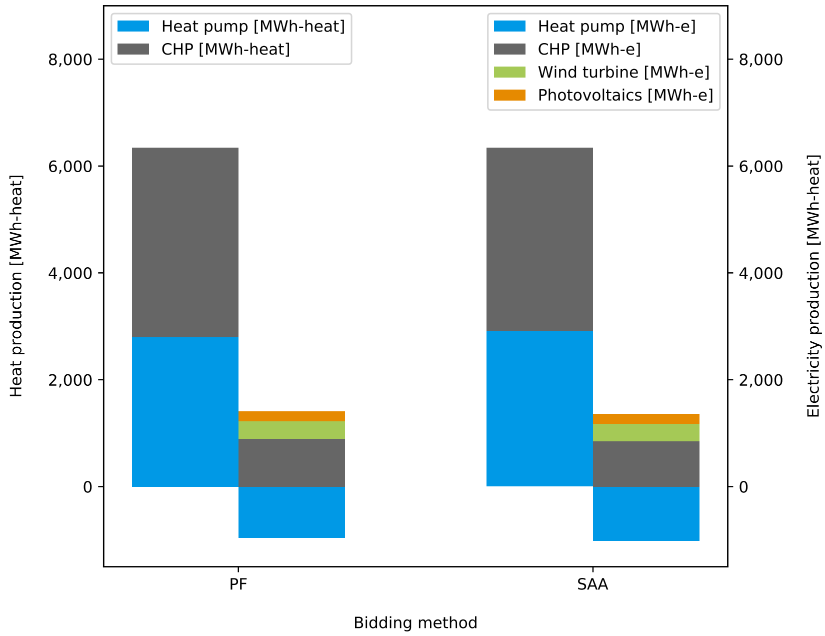

Figure 5.9. Heat production and electricity production of the energy conversion units at the district heating plant. A negative production is a consumption of electricity. The electric boiler and woodchip boilers are not shown, as they produced so small amounts that it cannot be visualized.

In Figure 5.9, the heat production, electricity production and electricity consumption of the energy conversion units can be seen. The figure is very similar to Figure 5.2, without participation in the regulating market.

Finally, in Table 5.1, the traded electricity, and the corresponding revenue and expenses, for doing so can be seen for each of the electricity markets.

	PK	SAA
Spot market [MWh-e]	-402	-289
Down [MWh-e]	159	170
Up [MWh-e]	200	222
Spot market [DKK]	-237,868	-198,951
Down [DKK]	16,874	12,540
Up [DKK]	-111,362	-135,732

Table 5.1. Traded electricity on the different electricity markets as well as the total expenses for each of the markets. A negative expense is the same as an income and a negative traded volume is sale of electricity.

As shown in Table 5.1, the method based on Sample Average Approximation sells netto less electricity in the day-ahead market than the reference, with an about 40,000 DKK lower revenue from this. However, because the electricity was not sold in the day-ahead market due to slightly suboptimal placement of bids, the capacity for participating in the up regulating market is higher. The method based on Sample Average Approximation is able to instead calculate optimal bids for participating in the regulating market, which makes up for the loss, causing the method to perform better than the reference.

It has now been shown, that Sample Average Approximation can be used to calculate very optimal bids for Assens District Heating, both when participating in the day-ahead market only, and when participating in the regulating market as well. However, in the analysis the minimum bidding quantity of 5 MWh-e for placing bids in the regulating market was omitted. The proportion of down regulating bids won below 5 MWh-e was for the Sample Average Approximation 13.1% of the total bids, while 44.2% of the won up regulating bids were below 5 MWh-e.

Chapter 6

Discussion

In the analyses, it was shown that the unit commitment resulting from having to place bids into the unpredictable electricity markets was often leading to higher operational expenses than the optimal unit commitment in hindsight. For the price-independent bidding method the operation led to 8.5% higher costs, while the method based on Sample Average Approximation typically led to the expenses being only a few percentages higher than the optimal unit commitment. A few percentages in difference may not seem like much, but if one considers the yearly expenses of all the decentral district heating plants in Denmark, the importance of good state-of-the-art bidding methods is apparent. While the price-independent bidding method generally performed poorly, an interesting observation from the analysis of the simple case could be made. By participating in the regulating market, it was possible to make up for the suboptimal bids placed in the day-ahead market. However, a method for placing price-independent regulating bids for the full case was not analyzed, and it therefore cannot be concluded whether this is valid for all cases.

The benefits of participating in the regulating market was generally significant, leading to reductions in the total operational expenses by 6-12% across the different analyses. Both up and down regulating bids were won in all cases. However, the assumption that bids of any volume can be submitted to the regulating market may challenge these results, as a large proportion of the bids were below the minimum of 5 MWh-e imposed by Energinet. Significant revenue could thus be obtained for a decentral district heating plant with small energy conversion units if these minimum constraints were lowered. Alternatively, the district heating plant should pool regulating bids together with other producers or consumers.

It was chosen to simulate the participation in the day-ahead market and the regulating market with activation bids only, due to rich data about these markets being available. However, in reality the districting heating plant could also place availability bids in the regulating market. Special regulation and the intra-day market were not included in the simulation either. There was a clear advantage of participating in two electricity markets, as poorly submission of bids in the day-ahead market could be made up for by placing bids in the subsequent regulating market. The value gained from participating in further electricity markets could be expected to be even higher. The method based on Sample Average Approximation presented in this report would not be able to calculate availability bids or participate in pay-as-bid markets. However, it does not seem improbable that the

MILP could be reformulated to include this.

The main objective of this report was to find a suitable way to place bids for the studied case of Assens District Heating. It was not possible to apply the heat unit replacement bidding method, but the method based on Sample Average Approximation proved to place extremely competitive bids, both for the simple and the full case. However, a large number of assumptions were made in the methodology that could impact the results of the research. It can be questioned whether the proposed method truly is a realistic bidding method, as it relies on scenarios generated by training data that includes the simulation period itself. However, it was not the scope of this report to dive into the complex field of forecasting weather data and electricity markets, yet it was necessary to have forecasts and scenarios to test the bidding methods. In order for the bidding method to be deployed at a real district heating plant, the method for scenario generation therefore has to be improved first.

Another important assumption is the choice of simulation period. The 4 weeks chosen constitutes a relatively small sample to make grand conclusions about the exact value of participating in the regulating market. It can also be expected that the different seasons of the year have different intricacies, that could impact the exact results presented in the analysis. However, the method based on Sample Average Approximation is very versatile as it relies on the generated scenarios and not a defined algorithm or decomposition of the problem by energy units as in the heat unit replacement bidding method. As long as the method for generating scenarios is able to provide good scenarios for the entire year, it is expected that the method based on Sample Average Approximation will keep calculating competitive bids.

While the heat unit replacement bidding method and price-independent bidding methods are fairly fast to compute, the method based on Sample Average Approximation revolves around solving a significantly larger MILP. The computational speed is of significant importance in a bidding context, as the plant owner would want to calculate the bids as close to gate closure for the bidding market as possible, in order to calculate the bids using the most recent information. In this report, the combination of using 50 scenarios, a rolling planning horizon of 5 days and a tolerance gap of 1% resulted in a computation time of roughly 2 minutes per stage in the MILP. This translates to 6 minutes of computation time for running the entire stochastic unit commitment problem for one timestep, as there are three stages in the MILP. A computation time of 6 minutes seems reasonable, as it would easily allow for placing regulating bids every hour, even for a more complex district heating plant than Assens.

The importance of good state-of-the-art bidding methods can be extended to more than just lowering the operational costs of the district heating plant itself. The sector coupling between the district heating sector and the electricity sector relies on the ability of the district heating plants to respond to price signals and thus provide load flexibility. For the analysis of the price-independent bidding method it was shown that it resulted in bids for purchase being made in hours with high spot prices, and bids for sale being made in hours with low spot prices. In the references and in the method based on Sample Average Approximation, this never occurred. A district heating plant should not purchase electricity when the spot price is high if it can be avoided, as the entire idea behind power-to-heat is to use excess renewable electricity production. It is assumed that the excess renewable electricity production is non-existent when the spot price is high. The method based on Sample Average Approximation also proved to cause the least imbalances between the traded electricity and the actual consumption and production. This method is therefore a crucial way to reduce the barrier for a successful coupling of the heating and electricity sector, thus leading to an energy system that can integrate larger shares of fluctuating renewable energy for the benefit of a more sustainable future.

Chapter 7

Conclusion

District heating plants face complex challenges in planning the optimal operation and bids in the electricity markets, as more uncertainties are introduced in the energy system due to an increased integration of fluctuating renewable energy. Assens District Heating is an example of a district heating plant, where the state-of-the-art heat unit replacement bidding method cannot be used to calculate optimal bids. An approach based on scenario generation and Sample Average Approximation is used to instead calculate the optimal bids for this case. Scenarios were generated for ambient temperature, aggregated solar irradiance, wind speed, spot prices and regulating prices and with these it is possible solve the stochastic bidding problem in a reasonable time for bids to be placed in the hourly electricity markets. The approach based on Sample Average Approximation submits a bidding curve for every hour, rather than just a single bid. This leads to operational expenses almost as low as for the references with perfect forecasts of the future prices. Of all the methods analyzed in this report, Sample Average Approximation results in near optimal operation in all cases and the method generally outperforms the much simpler price-independent approach. Finally, it is found that Assens District Heating can lower their operational costs significantly by also participating in the regulating market.

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